# A study on gesture keyboard performance, a comparison of dyslexic and non-dyslexic users.


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## Abstract

Many studies on text entry and their underlying motor skills have been conducted, in most cases these studies have focused on typing on a standard keyboard. However text entry on soft keyboards, which are used on touchscreens, has not been given the same amount of attention. This study aims to show how motor skill development tends to differ for people diagnosed with developmental dyslexia and how this influences their final performances when using soft keyboards. The way of recording and analyzing these learning processes for the development of motor skills are practically new to the field of HCI. Although the results of this study were found not to be significant this study has shown how nonlinear regression can be used as an analysis tool in the field of HCI.

*Keywords:* Gesture keyboards, text-entry, nonlinear regression, learning curves, dyslexia

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# 1 - Introduction

## 1.1 Introduction

The goal of this study is to determine if gesture keyboards are suitable for all users, and in particular people diagnosed with developmental dyslexia. The current situation will be discussed in light of multiple themes. This will start off with a general discussion of contemporary keyboard usage, followed by a brief review on the developments of keyboards over time. The third theme will be the developments in human computer interaction specifically designed for dyslexic users. The next theme that will be addressed is motor skills and their underlying systems, and how these might differ between dyslexic and non-dyslexic users. The last theme is on linear and nonlinear regression and which of these better portrays the learning effect that is found in motor skill developments. This introduction will be concluded with a short summary and stating the research question.

### 1.1.1 General introduction

In day to day life we are depending more and more on electronic devices and social media to stay up to date and interact with one another. These developments are represented in smart phones and tablets, for example Twitter, Facebook-apps and e-mail access but also GPS and digital calendars. Despite benefits, the usability and in particular the interaction with these devices is somewhat lacking. Touchscreens do not offer two-handed, eyes-free touch typing like a regular keyboard (Mackenzie, Zhang, & Soukoreff, 1999), for desktop systems QWERTY keyboards are the primary text input devices, however when transferred to mobile and or handheld devices functionality decreases. As substitute touchscreens offer a soft keyboard (also known as software keyboard or onscreen keyboard) which requires one handed, eyes-on tapping. This relies on quite a different motor skill (MacKenzie & Soukoreff, 2002) especially on smart phones, because of the size of the screen, text entry is reduced to single finger tap input. ‘’Since text entry is one of the most intensive and frequent human computer Interaction (HCI) tasks speed is a very important consideration’’ (Zhai & Kristensson, 2012, p. 91).

### 1.1.2 Developments in the field of text entry keyboards

An overview of the developments for smart phones is in order, to give an impression of the systems that were designed to enhance text entry speed. In the field of human-computer interaction multiple keyboard layouts have been developed (MacKenzie & Soukoreff, 2002) to increase text entry speed. These keyboard layouts were designed to optimize key position placement. By placing letters of frequently used words close to each other word input time is reduced. In a study by Mackenzie and Zhang (1999) optimized soft keyboards were compared to a soft keyboard using a QWERTY layout. Based on statistical analysis maximal text entry rates for experts were estimated. The expected text entry rate for an experienced user is higher for these optimized layouts compared to the regular QWERTY keyboard. However, becoming proficient in the use of new keyboards takes time, Mackenzie and Zhang refer to this as the walk-up entry rates for new designs (MacKenzie & Zhang, 1999). Despite expected speed increase for the optimized layout, using the familiar QWERTY layout on a soft keyboard will allow for an initial faster text input. This will make it difficult to get potential users excited about these new layouts. Indeed, when asked, participants indicated a preference for the familiar QWERTY layout (Lewis, LaLomia, & Kennedy, 1999).

Other means for increase in text entry speed have been developed that still use the QWERTY layout. Word prediction software can reduce the number of taps required to form a message. Based on the first few keystrokes/taps these prediction systems show a list of predicted words from which the user can choose. Research (Anson et al., 2006) has shown that word prediction on soft keyboards shows a noticeable increase in text entry compared to normal tap input. Further developments on word prediction have led to the word-gesture keyboard. These require even less finger taps to create a word, instead text entry is performed using a qwerty keyboard on which a finger can trace from letter to letter, based on this gesture word predictions are shown. Add to this that spaces between words are set automatically, with an average length of English words of 4.7 letters this requires 1 action less in every 5.7 keystrokes/taps (Zhai & Kristensson, 2012), and an increase in text entry rate is a realistic expectation. Furthermore in the analysis of 556 reviews of users of a gesture keyboard (Writingpad) 81.6% were completely positive. All in all developments on smart phone interaction have led to a soft keyboard still based on the QWERTY layout which allows both gesture and finger tap input.

These gesture keyboards are well received by smartphone users, their actual text entry speed however has not been studied extensively for these new keyboards. These developments are intent on better interaction with mobile devices and increase text entry speed up to a level that is comparable to that of a QWERTY desktop keyboard. As mentioned earlier new designs have walk-up entry rates (MacKenzie & Zhang, 1999) that need to be overcome in order to become a proficient user. Acceptance of new text entry methods has been halted many times partly due to this transition time (Eilam, 1989; Mackenzie et al., 1999; Noyes, 1983). Arguably this transition time is longer for people suffering from learning disorders such as people diagnosed with developmental dyslexia (DD). Dyslexia is commonly defined as ‘’ Individuals that have difficulties with accurate or fluent word recognition and spelling despite adequate instruction and intelligence and intact sensory abilities’’(Peterson & Pennington, 2012, p. 1997).

### 1.1.3 HCI applications for dyslexics

In the field of Human Computer Interaction (HCI) there have already been designs specifically developed for people diagnosed with DD. Some examples are presented below.

Web navigation, exploratory research has shown that dyslexics have specific needs when web browsing. While web design guidelines for dyslexic users exist, their own experiences had not been examined previously. This study shows that dyslexic users stick to navigation structures with which they are familiar. Expectations are that this will have implications on further development in web design (Al-Wabil, Zaphiris, & Wilson, 2007).

Computer programming, Development of drawing and thinking strategies to Enhance Computer Programming for people with dyslexia, though this is only a planned project it shows exactly the HCI improvements which would be useful for dyslexics. The theory is to use the brain’s visual-spatial sketchpad which might compensate deficits in short-term memory and phonological awareness. It is referred to as a spatial thinking strategy which could become an optional part of programming (Coppin, 2008).

Word processing, a study by MacArthur (1998) used a combination of speech synthesis and word prediction in treatment phases to improve word processing in children with learning disabilities. Legibility and correct spelling increased with 90-100% compared to the baseline.

This shows that people who suffer from developmental dyslexia have specific difficulties in HCI and that these difficulties can be addressed. The question that remains is if these sorts of problems exist for dyslexic smartphone users, particularly in the case of text entry. To determine whether or not this is the case the underlying systems of text entry, such as learning and word representation, must be examined.

### 1.1.4 Text entry as a motor skill

Learning to use a new keyboard (layout) is in basics the same as learning how to type, it requires the development of a motor skill. "Motor skill learning is the process by which motor skills are becoming effortlessly performed through practice" (Savion-Lemieux & Penhune, 2005, p.423) Typing is a good example of motor learning as both the actions and the cognitive steps are hierarchically structured (Crump & Logan, 2010). This structure makes it more comprehensible how motor learning takes place. This is shown in figure 1.

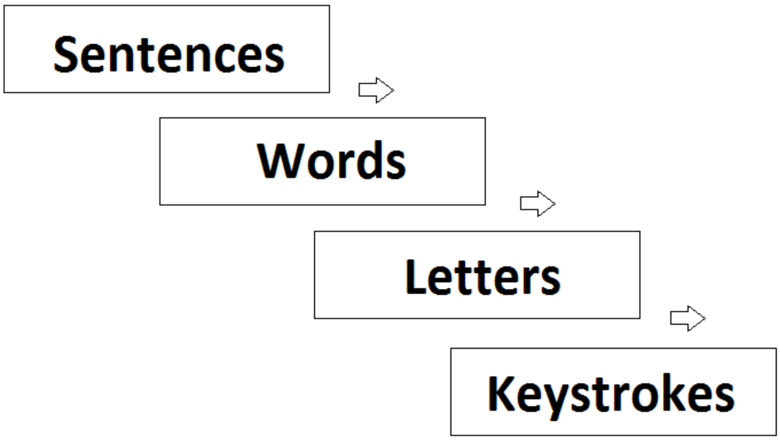


*Figure 1*. Levels of representations as used in typing.

Typing is dependent on pre-existing language skills. People before learning how to type must have already learned how to read and write, they know which letters constitute a word and how to organize these words into sentences. Studies by Rieger (2004, 2007) have shown that single letter information for experienced typists activates keystroke execution for particular letters. Shaffer (1975) states that the intention to type and perform keystrokes is argued to be organized hierarchically with higher level intentions to type words and sentences controlling lower level processes through which words are converted into ordered keystrokes. Shaffer (1976) describes typing as the ability to fluently coordinate intention with performance.

Research has shown how fluent this truly is, it is not just a matter of fluent coordination but a parallel activation of constituent letters and keystrokes which make up the representations on word level (Crump & Logan, 2010). These representations, especially on word-level, may be the key to becoming proficient in the use of a new keyboard. But in order to determine why the transition time for people suffering from DD is longer, these representations must be further examined.

Representations of words consist of sound (phonetics), spelling (orthography) and meaning (semantics). On the subject of developmental dyslexia (DD) learning problems have been studied extensively. Research (Pennington, Cardoso-Martins, Green, & Lefly, 2001) has shown that people diagnosed with DD have a deficit in phoneme awareness (word recognition). Many recent studies support this fact; Frith (1999) mentions a neurological deficit that affects phonological representations. Combined with a deficit in orthographic coding skills (Bowers, 1995; Cornwall, 1992; Manis, Seidenberg, & Doi, 1999) this supports the theory that people diagnosed with DD are impaired when it comes to constructing and using word representations. Comparing these two groups, dyslexic and non-dyslexic people, is done by measuring their learning process over an extended period of time. Learning a new motor skill is based on the principle of Ebbinghaus (Young, 1985) in which repetition is key. Keeping track of measures on performance time during practice will, over time, return diminished values. This is known as the power function of practice (Snoddy, 1926).

#### 1.1.5 Reaching optimal performance

An example of this learning trend in motor skills is learning how to swim. When children learn to swim, they breach the distance of the pool faster with every lesson. The mean performance of swimming speed of a class of children over a few weeks would show a consistent improvement over time. For professional swimmers at the start of their career this would not be the case. The expectations are that their performances would increase rapidly at first, during which they break their personal bests every other week, after which their performance still increases only less rapidly. As they reach their optimal performance it requires months of training to improve by even a hundreds of a second. These stages are also applicable to the development of typing skills.

Searching for optimal performances requires that, through repetitive training, a learning effect is established. Repetition would consist of multiple training sessions. Measuring the performance in time allows for examination of the learning effect. By depicting these measurements a learning curve can be created. These learning curves show the improvement of performance over time during training sessions. These curves were already used by Kuhlmann in 1909 to determine the amount of conscious thought during typewriting. In this study he showed that conscious thought slows typewriting performance and as the skill is trained during practice the typewriting performance improves (Kuhlmann, 1909). In these learning curves there are three ways of detecting a learning effect. The first is shown by a flattening of the line which indicates that an optimal performance is reached. The second is found by subtracting the initial performance time from the optimal performance time, which shows the overall learning effect of the training. The third is found by averaging the difference in performance per training, this shows the learning rate.
These three indicators can be used to determine if individuals or groups differ in their development and application of motor skills.

The path to becoming an experienced user of a new keyboard is an interesting part in the usability assessment of a new tool. This is however rarely analyzed in the field of HCI. The three indicators that are mentioned before can be used to determine how long it takes to become an experienced user, what the difference is between a novice and an expert and finally how fast these experienced users can become.

### 1.2 Research Question

This study wishes to show how learning curves can be of added value as a analysis tool in the field of HCI. This could give direction to follow-up studies in this same domain and could therefore be considered a pilot study. To illustrate this functionality of learning curves this study will focus on the following research question

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*“To what extent does the optimal performance of dyslexic individuals differ from non-dyslexic people while using the Slide-It function on an android control system?”*

These optimal performances are found by measuring performance time over an extended period of learning how to use the Slide-it gesture keyboard. These are then compared for each of the indicators of learning.

# 2 - Method

## 2.1 Participants

This experiment initially involved 10 participants. During the analysis three participants were dropped, two of them because their data did not show a clear learning curve and a third because its data did not converge to either statistical model. All remaining seven participants have finished high school and are currently attending further education or have obtained a certificate over the last few years. The participants were divided into two groups and the first consisted of three dyslexic individuals (one man and two women) that were all Dutch, with ages ranging from 22-26 with a mean of 24. Of the dyslexic partakers one had little experience with using Swype and two of them had quite a lot of experience in using Swype. The second group consisted of four non-dyslexic individuals (four women) of which two were Dutch and two were German, with ages ranging from 22-26 with a mean of 25.

## 2.2 Design

This experiment was setup as a repeated measures design. The participants were asked to repeat the same 10 sentences during 30 blocks. During each Block they were asked to fill in the 10 sentences and then move on to the next block. Each sentence comprised of four to seven words. For the German participants these sentences were translated into German while trying to stay as close to the original Dutch lines as possible. After every 5 blocks participants were granted the opportunity to take a short break, of approximately 5 to 10 minutes, in order to relax. After the participants had executed 15 blocks they were urged to take a mandatory break for up to 30 minutes. During this break the experiment supervisor prepared the setup for the second half of the experiment. The entire experiment lasted between three and four hours. Returning to the subject of the sample size, a group of seven participants is quite small, even for a study that uses a repeated measures setup. However the sample size is less relevant in this design, seeing as this experiment is designed as a pilot study on learning curves in HCI research. The most important aspect in this design is to gather data that can be analyzed using learning curves. With 30 measurements per participants over a period of three to four hours it is almost guaranteed that a learning effect is found in the collected data.

### 2.3 Apparatus

The data input by the participants was performed using Slide-It in the Bluestacks Android Emulator. Bluestacks was displayed on a Dell Precision M4500 (i7-940XM) Notebook. The recording, observing and extraction of this process were conducted using Morae_3.3 (Recorder, Observer and Manager).

### 2.4 Task

The participants placed their hand on the mouse and on the screen in front of them a qwerty-keyboard was displayed. The sentences they were required to enter were presented on a piece of paper which lay next to the laptop. For each separate word they placed the mouse-cursor on the first letter of that word, clicked and hold the left mouse button while moving the cursor across the letters of the word. When the cursor was atop the last letter of the word they let go of the left mouse button. Based on their movements the computer showed suggestions from which they could pick a word. Participants would click on the right suggestion and incase the first suggestion turned out to be correct the participant could immediately move on to the next word.


*Figure 2*. Print Screen view of Slide-It suggestion in Bluestacks (Dasur Ltd. © 2011).

The program would fill in any spaces or capital letters. After each sentence the partakers would click on the enter button displayed on screen and start the next sentence on a new line. After entering 10 sentences (corresponds with one Block) the participants would click on the line beneath the following block and start entering the same 10 sentences again.

### 2.5 Procedure

Administration of the experiment was conducted in a controlled environment to ensure participants were not distracted from the task at hand. Before commencing with the experiment, partakers were asked to fill out a questionnaire which covered topics such as age, nationality, education level and experience with keyboard functions such as Swype and Slide-It. After the participants were seated in front of the laptop they received instructions which they were asked to read carefully. As the partakers were either Dutch or German the instructions were offered in both languages (see appendices D and E). Firstly was described how the entry of words was supposed to be executed. Participants were asked to fill in a test sentence, in order to judge whether they had understood the instructions or not. This sentence was only used for practice and did not appear anywhere else in the experiment. Participants were then given the opportunity to ask questions. The next segment of the instructions showed a description of the experimental setup. Two parts, each containing 15 blocks, were separated by a mandatory break for approximately 30 minutes. Partakers of the experiment were required to fill in 10 sentences (Appendices F and G) per block. Optional breaks of approximately 10 minutes were scheduled after every 5 blocks. In the final segment of the instructions four pointers were provided. The translation is shown below:

1. Try to finish each sentence as quickly as possible
2. Do not correct your mistakes but proceed with the next sentence
3. After finishing each sentence click on the enter button and proceed with the next sentence on a blank rule
4. You are not required to fill in punctuation marks

These 4 rules were given for multiple reasons; most importantly to make sure the participants executed the task as similar as possible. Especially the first two rules ensured a smooth task execution. Rule three was added to assure that the collected data would be clear and organized. An orderly data file minimizes the chance of human error during the analysis. The fourth and final rule was intended to keep this research solely focused on word production. The participants were then given a test sentence to enter; this sentence was shown on the instruction sheet and did not appear anywhere else in the experiment. After reading through the instructions participants were given the opportunity to ask questions.

**2.6 - Analysis**

The structuring of the data was performed via a series of consecutive operations using different programs. The first step was accessing the individual recorded files of Morae for each participant, this was done using Morae Manager. These files contain a video recording of the desktop for the time of the experiment, a time line for the duration of the experiment and a list of times relative to the starting of the recording which show at which moments the left mouse button was clicked. Starting times per block were determined by isolating the recorded mouse click for the first word of that block. End time was determined manually by use of the video recording. From Morae Manager all start and end times of each block, per participant, were manually extracted to the program Microsoft office excel 2007. Calculating the time duration of each block was done by subtracting the start time of each block from its end time. The final step was transferring these duration times per block to PASW SPSS Statistics 20.

In SPSS simple scatter plots were used to plot values of one continuous variable against another, these were created for each participant. These plots depict their performance time (in seconds) set against the duration of the experiment in blocks (training sessions). Next Loess fit lines were added to display the trend of the data over time. See appendix A for a step-by-step tutorial on curve plotting.

The next step was to fit a nonlinear regression model to each participant. In nonlinear regression the most commonly used models contain either an exponential or a power function. The power function is based on the 'power law of practice' and is used to show if data contains a learning curve (Aynalem, 2007). However in recent years concerns were raised about the usage of the power curve, an alternative was introduced namely the exponential function (Heathcote, Brown, & Mewhort, 2000). Both functions are shown below.

- Power function g(f) = f ^-c
- Exponential function g(t) = e ^-ct

These were then added to an asymptotic regression model which provided the model expressions as shown below (as expressed in SPSS).

- Power model expression: y = b1 + b2 * b3**x
- Exponential model expression: y = b1 + b2 * exp(b3 * x)

For both models y is the dependent variable in this case measured performance time, x is the independent variable trials (moments of measurement), b1, b2 and b3 are the parameters. Parameter b1 is the asymptote or the optimal performance at the end of the training. Parameter b2 is the overall regression which shows the total learning effect of training. And parameter b3 is the learning rate constant, in this case the average improvement of performance between each trial. Both models (power and exponential) were fitted to each participant however neither showed a clear better fit in terms of variance explained (R-squared values). The exponential model however provided one additional case in which a participants' data converged to the model, this is why the exponential model was used to determine the final parameter estimates.

As this study aims to compare the optimal performance for the dyslexic and non-dyslexic group parameter b1 will be used to compare their performances. The other two parameters, though of great importance in the learning process, are in this case added to the model to explain a higher proportion of the variance.

The final analysis of comparing the two groups parameters was performed using an independent samples t-test with condition (dyslexic or non-dyslexic) as the between subjects factor. For a step-by-step tutorial on comparing two nonlinear regression models see appendix B.

## 3. Results

In this section the learning curves for each participant will be displayed. Dispersion of the data is depicted using scatter plots, which were created for each participant individually. These plots contain two loess curves the first is a performance curve, which displays the trend of performances during the experiment, and an estimated curve which is based on the estimations of the exponential nonlinear regression model. For each condition a paneled chart was created containing the learning curves per participant. Figure 3 shows the paneled chart for the subjects in the dyslexic condition. Figure 4 contains the paneled chart for the subjects in the non-dyslexic condition. The results for the two samples independent t-test are examined further on.

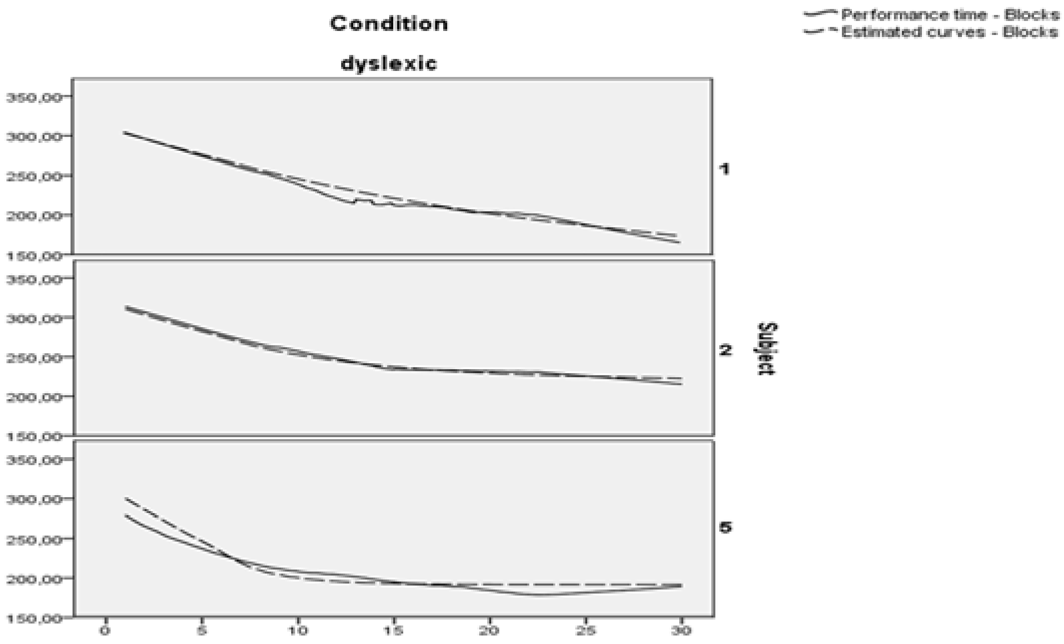


*Figure 3*. Paneled chart for the dyslexic group.

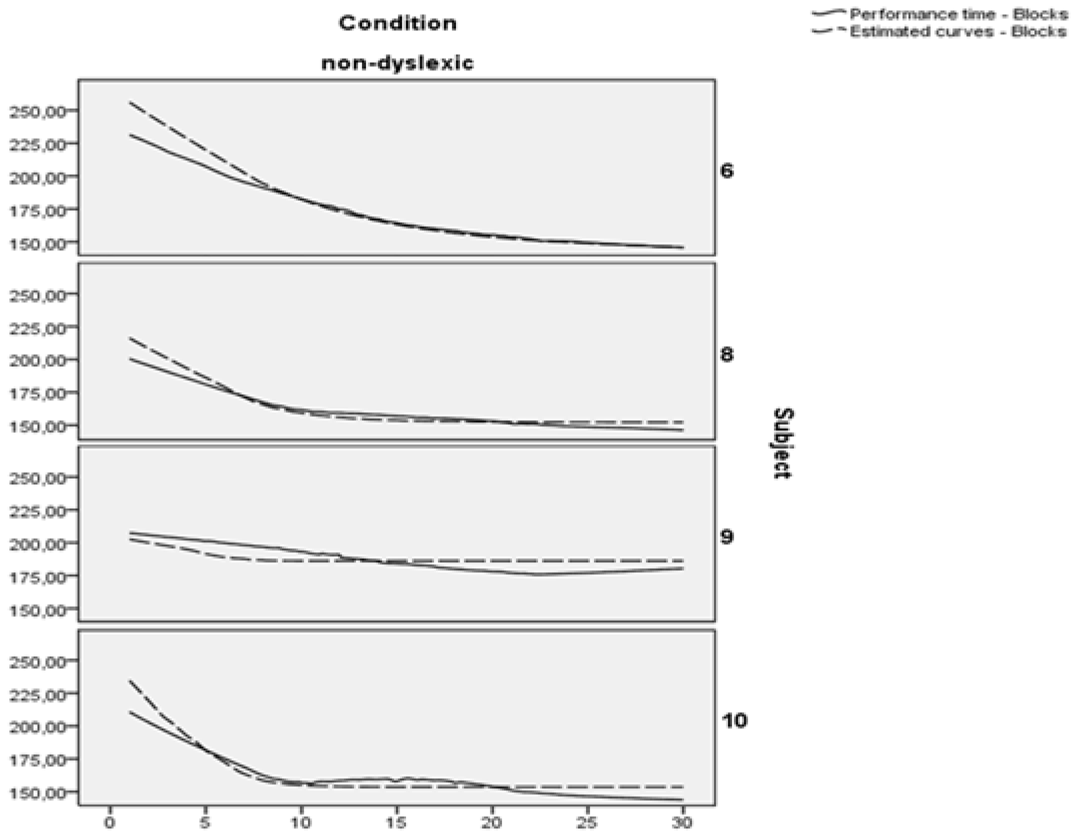


*Figure 4*. Paneled chart for the non-dyslexic group.

The group means of the parameter estimates are shown in table 1. Parameter b1 is the estimated value for the asymptote and will determine whether the optimal performance for the non-dyslexic differs significantly from that of the dyslexic group. Parameter b2 estimates the value for the overall learning effect by comparing the least sum of squares with and without training. In other words it shows the amount of improvement in performance caused by training. The estimated values for parameter b3 controls the rate at which the optimal performance is reached this is called the rate constant.

Table 1

*Parameters mean values summary the means of the final parameter estimates are shown for each group (dyslexic and non-dyslexic)*

| Condition | N | Parameters | Mean | Std. Deviaton |
|---|---|---|---|---|
| Dyslexic | 3 | b1 | 179,6348 | 47,52905 |
| | | b2 | 175,0454 | 59,27263 |
| | | b3 | -0,1838 | ,16952 |
| Non-dyslexic | 4 | b1 | 159,5206 | 18,24017 |
| | | b2 | 209,6473 | 95,00243 |
| | | b3 | -0,5397 | ,40414 |

Shown below in table 2 are the results of the independent samples t-test. The two groups (dyslexic and non-dyslexic) are compared on the mean values for their final parameter estimates. All values in the t-test for equality of means were calculated by comparing the dyslexic to the non-dyslexic group.

Table 2

*Independent Samples T-test shows the differences found in the parameters (b1, b2 and b3) between the two groups (dyslexic and non-dyslexic).*

| Parameters | T | df | Significance | Mean Difference |
|---|---|---|---|---|
| b1 | ,793 | 5 | ,46 | 20,11 |
| b2 | -,549 | 5 | ,60 | -34,60 |
| b3 | 1,408 | 5 | ,22 | ,36 |

Note. Scores are based on comparison of non-dyslexic to dyslexic (Dyslexic – Non-dyslexic)

All results were compared to a 5% significance level. Meaning that there was no significant difference on the scores of parameter b1 (optimal performance) for the dyslexic (M=179.63, SD=47.53) and non-dyslexic (M=159.52, SD=18.24) conditions; t(5)=.79, p=.46. These results give no suggestion on if a difference in optimal performance between the two groups exists.

This is the same for parameter b2 (overall learning effect), no significant difference was found between the dyslexic (M=175.05, SD=59.27) and non-dyslexic (M=209.65, SD=95.00) condition; t(5)=-.55, p=.22) This means that it could not be determined if one of the groups improved their performances more than the other during the training.

For the last parameter b3 (learning rate), again no significant difference has been found between the dyslexic (M=-.18, SD=.17) and non-dyslexic (M=-.54, SD=.40) conditions; t(5)=1.41, p=.22. Meaning that it could not be determined if one of the groups improved more and thus faster per training session.

It is the parameter for the asymptote (b1) that shows the optimal performance. The other parameters (b2, b3) will firstly be discussed to determine if other differences between the groups have been found. The parameter for the overall learning effect (b2) shows that the influence of training on diminished returns is greater for the non-dyslexic group (20.114 seconds). This means that performance of the non-dyslexic group, if results would have been significant, had improved more over the duration of the training sessions. This would have supported the notion that people diagnosed with DD are impaired on some motor skills that require text-entry due to their lack of phonemic awareness (Pennington et al., 2001). This is again the case for the learning rate constant, if the results found would have been significant, for the non-dyslexic group it is again higher (0.356). Meaning that the speed at which the participants improved their performances between training sessions was on average higher than that of the dyslexic group. This learning rate constant could have been used to indicate which group was quicker at adjusting to usage of a gesture keyboard. In summary non-dyslexic group has on average a higher improvement per block and the overall effect of training on performance is again higher for the non-dyslexic group. These results however are not significant on a 5% significance level.

When comparing the asymptotes (parameter b1) of both groups it shows that the optimal performance of the dyslexic group is 20.11 seconds (179.6348 – 159.5206) higher than that of the non-dyslexic group. Although this result is also not significant it is interesting to see what the indications would have been if it would have been found to be significant. This difference in optimal performance would have meant that the dyslexic group requires, on average, an additional 20.11 seconds to finish a block (training session). This is however the difference per block, by breaking it down to the sentence level a more real life setting is shown. For the dyslexic group the optimal performance time per sentence is approximately 17.96 seconds (179.6348/10). The non-dyslexic group has an average optimal performance time of 15.95 seconds (159.5206) per sentence. Comparing these two average scores on the sentence level shows that the non-dyslexic group is approximately 2 seconds (17.96-15.95) faster when they reach their optimal performance level. Using the score of the non-dyslexic group as norm these 2 seconds represent a difference of 12.5%. If the speed of text entry is truly important as stated by Zhai & Kristensson (2012) this difference of 12.5% is quite sizable and worthy of further investigation.

# 4 - Discussion

## 4.1 Discussion

First will be discussed why no significant results were found during this study. Furthermore as this is a pilot study this section will also focus on the implications of using nonlinear regression as a way of analyzing the data.

The design of this study was not primarily focused on finding find significant results, so it comes as no surprise that the research question cannot be answered. If the aim was to find results that would be applicable to a population the sample size should have been greater than was used in this study. If a follow-up study would be designed to answer this research question it would be wise to expand the amount of subjects as this will enhance the odds of finding significant results. As mentioned before two participants were excluded based on lack or distortion of their learning curve. Increasing the sample size would also allow for more flexibility if participants have to be excluded from the analysis. Seeing as, in this study, another participant had to be excluded from the final analysis due to a lack of convergence to the model it is also advisable to increase the length of the experiment. This would allow more participants to reach their optimal performance in the duration of the experiment. This way initial parameter values could be better assessed. And as convergence is most likely to occur if initial values are close to the least-squares estimates (Ratkowsky & David, 1990), this would increase the chance for the data of each participant to converge to the model.

In this study the data has been found to contain learning curves. The paneled charts (figures 3 and 4) clearly show a steep learning trend at first and a flattening of the line over time. This is consistent with the assumptions made in the introduction about nonlinear regression and its fit to motor learning. One example on how learning curves can be used in the field of HCI is shown in this study by trying to answer the research question.

*“To what extent does the optimal performance of dyslexic individuals differ from non-dyslexic people while using the SlideIt function on an android control system?”*

With the asymptotic regression model used in this study these optimal performances are directly measured by the first parameter b1. Optimal performances can be used to assess the usefulness of a device. Meaning that compared to previous designs a new design that allows for faster text input will most likely be considered more productive by smartphone users. However there are more ways to use nonlinear regression in the field of HCI. An example of this is its functionality in user friendliness assessment. For instance the adaptation of new designs, as is mentioned in the introduction the walk up entry rate (MacKenzie & Zhang, 1999) plays a vital part in the acceptance of new designs. Learning curves can be used to indicate how long people take to become familiar to this new design. Sticking to the asymptotic regression model, analyzing the learning rate and pinpointing the moment where the flattening of the curve begins would show this walk up entry rate. If a new design has a short walk up entry rate and people can get accustomed with minimal effort this will positively influence their view on user friendliness.

This study has shown how learning curves and nonlinear regression can be used as a way of analysis in the field of HCI. The arguments made for its function in usability assessment show how it could be of added value as an instrument in the HCI research toolkit. However this study is not exhaustive and in order to find out how and in which situations this tool could be best implemented requires further exploratory research. The two step-by-step tutorials (appendices A and B) on how to create learning curves and perform nonlinear regression have been added to give incentive for future HCI studies to consider this way of analysis.

### 4.2 limitations

One limitation of this study is the absence of a control group for the gesture (soft) keyboard. Without a control group using a standard keyboard it is not possible to determine if a gesture keyboard, which is based on word prediction, actually allows for faster text input as was suggested by Anson et al (2006) in the introduction. This control group would preferably consist of both dyslexics and non-dyslexics who would use a basic tap (soft) keyboard. This could be used to create a baseline, for each condition, that shows the optimal performance per group on a tap keyboard. Comparing the optimal performances for the gesture keyboards to this baseline would show the added value for gesture keyboard software for people in either condition. To see whether dyslexic people benefit just as much from the gesture keyboard would be interesting. With approximately 5-12% of the world’s population having problems with both reading and writing, which is consistent with dyslexia (Katusic, Colligan, Barbaresi, Schaid, & Jacobsen, 2001), developing a soft keyboard specifically for this group would appeal to a large number of consumers.

One final limitation that needs to be discussed is the reliability of the collected data. As is described in the method, participants were asked to input sentences using Slide-it, whilst reading these sentences from a piece of paper. The recordings of the experiment were set up to measure the time from the first movement on the first sentence of a block. Determining when a participant had finished a section of the training was done by hand using the video files of Morae Manager. Initially it was intended to determine this per sentence, however due to lagging in the video files it was necessary to change this to measurement per block. This also made it practically impossible to filter these measurements to just gesture movements. Meaning that the time necessary for reading the sentences during the block were not taken into account. In other words the difference found between the two groups might be solely based on the extra time dyslexic participants needed to read the sentences. This has severe consequences for the validity of this study. Participants did indicate that they no longer read, but only glanced at, the lines after the second or third block. This however leaves to much uncertainty. A possible solution to this problem might be presenting the sentences audibly, were it not for the fact that dyslexics are impaired on phonological processing (Snowling, 1995). Phonological awareness (part of phonological processing) is crucial in mapping alphabetical symbols to sound (Vellutino, Fletcher, Snowling, & Scanlon, 2004). This means presenting the sentences audibly could create the same problem, namely measuring the extra time dyslexic participants require to process the sentences. Another possibility is to use a different recording setup which allows for time measurements on sentence or word level. By starting the recording at the first ‘gesture’ and stopping it when the last ‘gesture’ is finished, accuracy of the measurements would be strongly improved.

### 4.3 Conclusion

In conclusion, the results show a tendency in favor of the non-dyslexic group as their mean scores for learning rate, overall improvement and optimal performance are higher. However due to lack of significance in the results of the analysis, the research question cannot be answered. It is not proven if the optimal performances for the dyslexic and non-dyslexic group differ significantly. As discussed the sample size of this study was too small and validity of this study was compromised by not excluding reading time from the measurements. However this research question has provided an example of how learning curves and nonlinear regression can be used as an analysis tool for HCI research. Arguments have been made for its value in usability assessment. It must be mentioned that this has only been shown for the case of motor skill development. Further exploratory research is necessary to assess how to best implement this analysis tool in the field of HCI.

# 5 - Recommendations

If this study were to be repeated the limitations and possible solutions discussed should be examined carefully. For future studies on (gesture) keyboards it should first be clarified what motivates people to try out and accept new designs. Other keyboard layouts, as discussed in the introduction, could provide a higher optimal performance on text entry than the regular QWERTY layout. As mentioned in a study by Mackenzie and Zhang, however, these new layouts are initially less productive compared to the familiar QWERTY layout, which Mackenzie and Zhang refer to as the walk up entry rate for new layouts. However a study by Zhai & Kristensson (2012) states that this familiar layout is inefficient for gesture text input because it frequently requires gestures over relative long distances on the screen. These studies have shown that the familiar QWERTY layout is not the optimal layout, especially for gesture text entry, but that before people become adequate at using a new layout they must first overcome a walk up entry rate. However none of these studies seem to address what the users of the keyboards prefer. This calls for an exploratory research to determine what users think about their keyboard layout and perhaps what would motivate them to become proficient in using another layout.

As is addressed in the introduction, gesture keyboards are the next step in word prediction software. According to Crump & Logan (2010) typing is an example of how thoughts are directly linked to performing a motor skill. The thought of a person is to create a word consisting of letters and the motor skill performs the corresponding keystrokes. This view on typing may however be too narrowly minded. Other mechanisms play a part in certain situations. One example is the chunking phenomenon (Sakai, Kitaguchi, & Hikosaka, 2003) this entails breaking down a sequence of letters or numbers into chunks. An example of this is the way humans memorize a license plate, for instance 51-NV-PR, this is not done per number or letter but in this case most likely in three chunks of two (that is 2-2-2). There has already been a study that investigated chunking in gesture keyboard usage and predicts an increase of performance of 20%. This study however used a gesture keyboard that only allowed for gesture input in two-character chunks (Isokoski, Martin, Gandouly, & Stephanov, 2010). It would be interesting to know if chunking is still used when text entry is performed on a gesture keyboard (such as Slide-it) that allows for full word input in a single gesture. Would the gesture for a word be mentally prepared as a single motion or also be chunked into smaller/shorter units? It is thought that chunking only occurs if users are more familiar with a task (Verwey & Abrahamse, 2012). This means that it is recommendable for studies on optimal performance to take chunking into account.

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# 7 - Appendices

## Appendix A

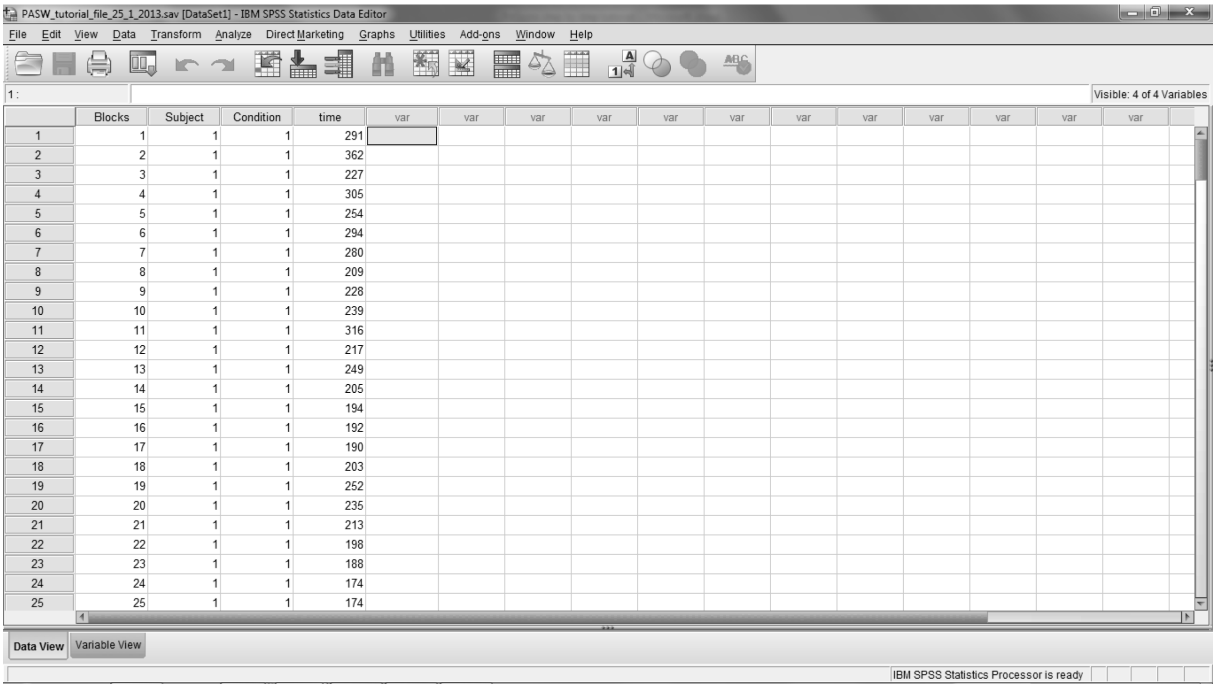
## Tutorial 1: learning curves

Nonlinear regression is often used to describe and compare learning effects. The first tutorial, on paneled charts, is used to assess the usefulness of data. It gives an indication of which parts of the data can be used for nonlinear regression. The second tutorial, on nonlinear regression, shows how to perform and compare two different model expressions of asymptotic regression in IBM SPSS 20. If you wish to know whether your data shows nonlinearity plot the data as is described in the first tutorial. If the line shows strong curvature, nonlinear regression is most likely the correct tool of choice. For more information on nonlinear regression and its application look at Handbook of nonlinear regression (Ratkowsky & David, 1990) or Nonlinear regression analysis and its applications (Bates & Watts, 1988).

As is stated above we search the data for a learning effect. A few basics on learning effects, in regression this is shown as the relationship between the dependent and independent variable. To determine whether a learning effect has taken place one looks at the change in performance (dependent) over a period of training (Independent). The first tutorial shows how to determine which participants show a learning effect in their data.

*Step 1: DataSet*

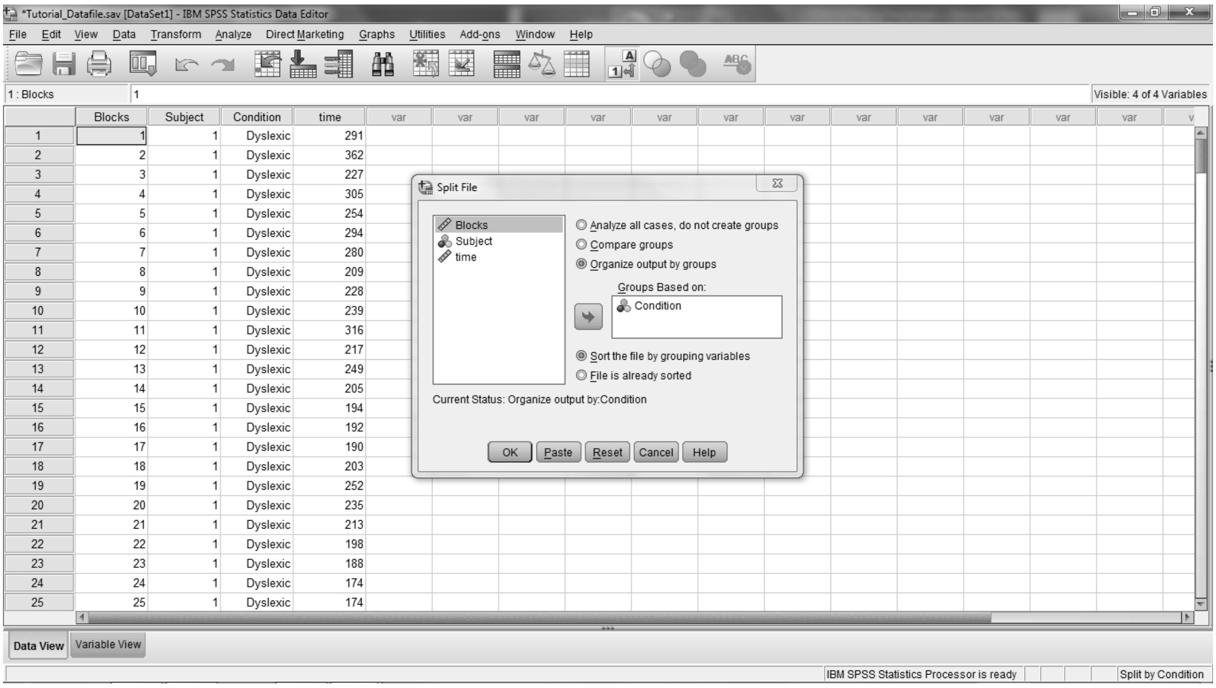
First displayed is the data file with the four original variables. In this case it contains the Blocks, these are the measuring moments, 30 per participant; Subject number; condition, 1=Dyslexic, 2=Non-dyslexic; time, amount of time the participant needed to finish the block (expressed in seconds). The topic of this research is the relationship between training (30 Blocks) and the learning effect on (performance) time (reduced values on the dependent variable). Plotting the data per participant shows their improvement over time.




| | Blocks | Subject | Condition | time |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 291 |
| 2 | 2 | 1 | 1 | 362 |
| 3 | 3 | 1 | 1 | 227 |
| 4 | 4 | 1 | 1 | 305 |
| 5 | 5 | 1 | 1 | 254 |
| 6 | 6 | 1 | 1 | 294 |
| 7 | 7 | 1 | 1 | 280 |
| 8 | 8 | 1 | 1 | 209 |
| 9 | 9 | 1 | 1 | 228 |
| 10 | 10 | 1 | 1 | 239 |
| 11 | 11 | 1 | 1 | 316 |
| 12 | 12 | 1 | 1 | 217 |
| 13 | 13 | 1 | 1 | 249 |
| 14 | 14 | 1 | 1 | 205 |
| 15 | 15 | 1 | 1 | 194 |
| 16 | 16 | 1 | 1 | 192 |
| 17 | 17 | 1 | 1 | 190 |
| 18 | 18 | 1 | 1 | 203 |
| 19 | 19 | 1 | 1 | 252 |
| 20 | 20 | 1 | 1 | 235 |
| 21 | 21 | 1 | 1 | 213 |
| 22 | 22 | 1 | 1 | 198 |
| 23 | 23 | 1 | 1 | 188 |
| 24 | 24 | 1 | 1 | 174 |
| 25 | 25 | 1 | 1 | 174 |

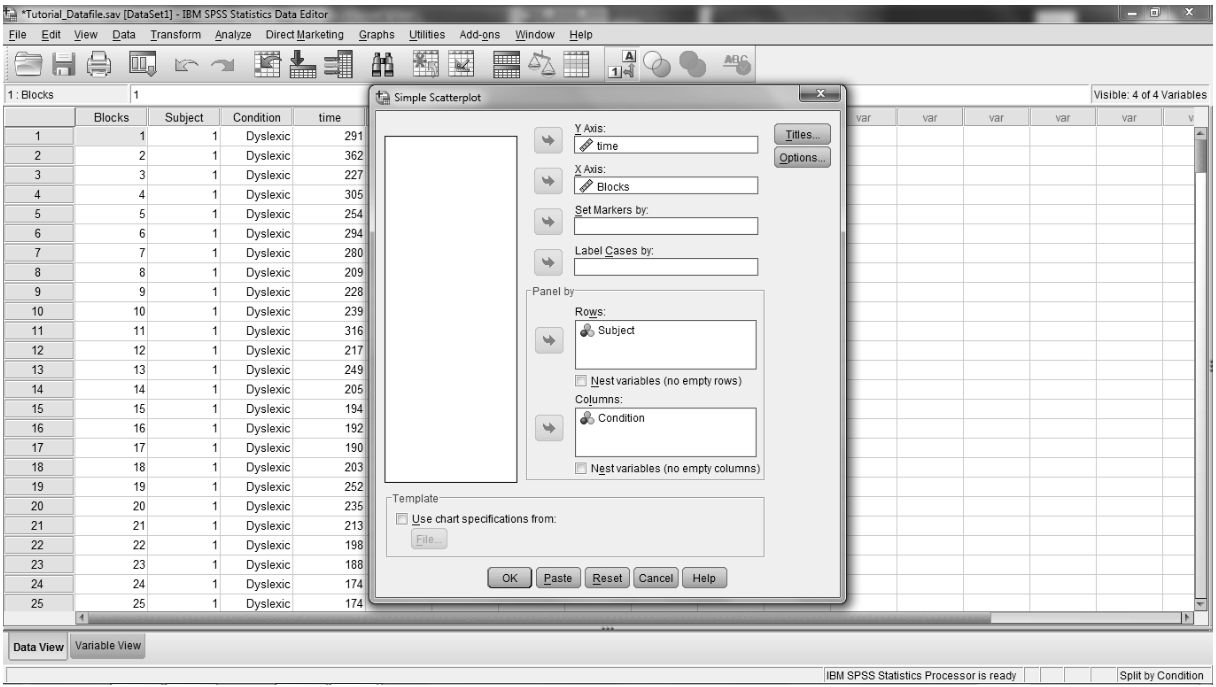
*Step 2 : Split File*

The second step to be taken is to find out if the data of all participants show the expected direction. The easiest way to determine this is to plot the data per participant in a simple scatter plot. To keep this organized it is advisable to use a paneled chart. Furthermore to prevent blank plots (in SPSS) in the paneled chart it is best to create one for each condition using the Split File command: Data → Split File… In the pop-up screen select the options Organize output by groups and Sort the file by grouping variables. Enter the Condition variable as the Groups based on: as is shown below.

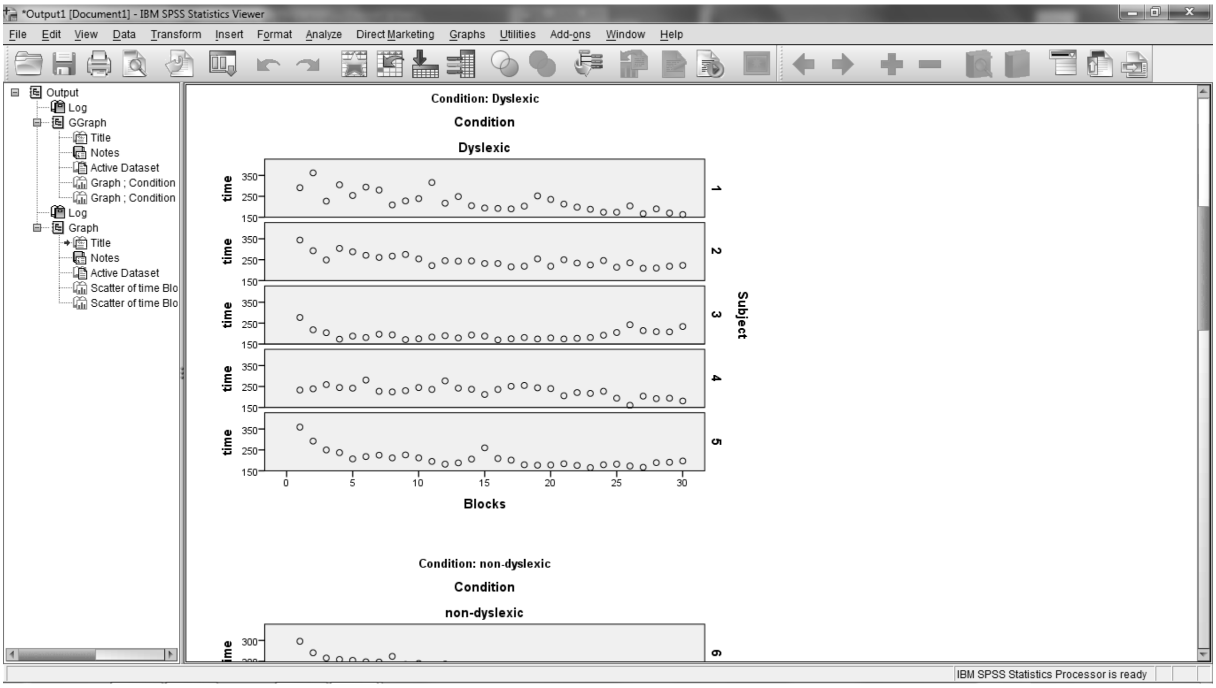



*Step 3: Paneled chart*

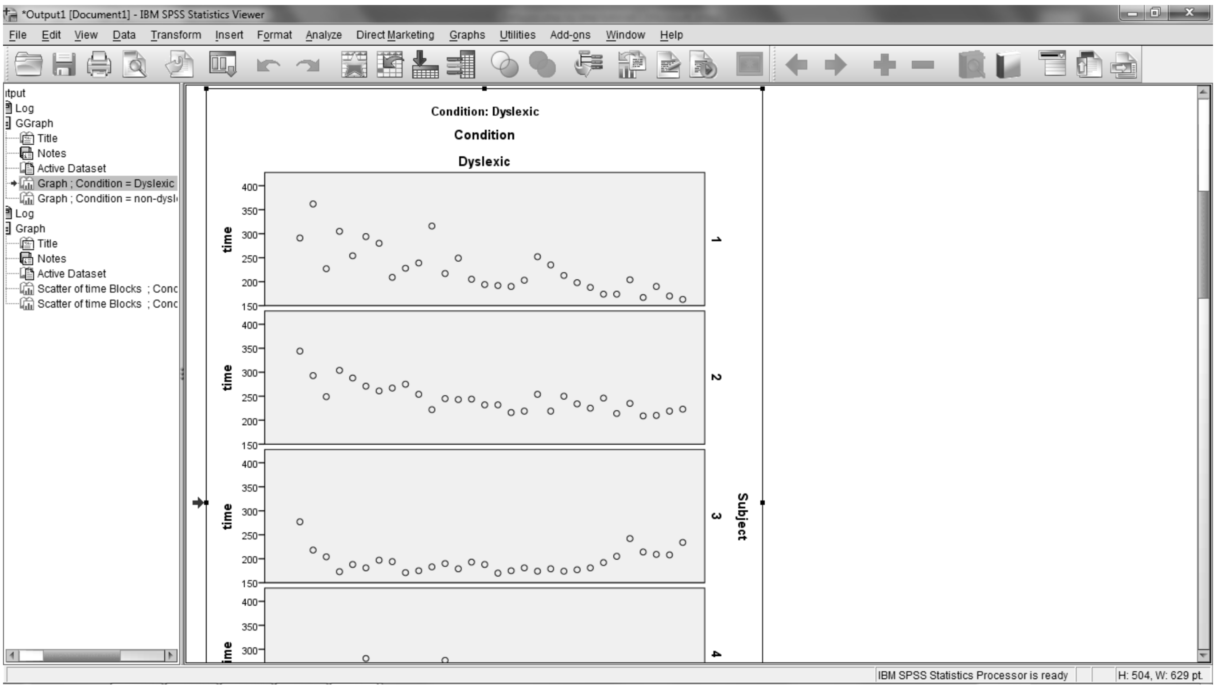
The setup for a paneled chart is simple: Graphs →Legacy dialogs → Scatter/dot.. in the following pop-up screen select Simple Scatter and click on Define. Place the dependent variable (time) on the Y Axis and the independent variable (Blocks) on the X Axis. In Panel by, select the Subject variable for Rows and Condition for Columns.



Now click on OK and the output should look like the image that is shown below.



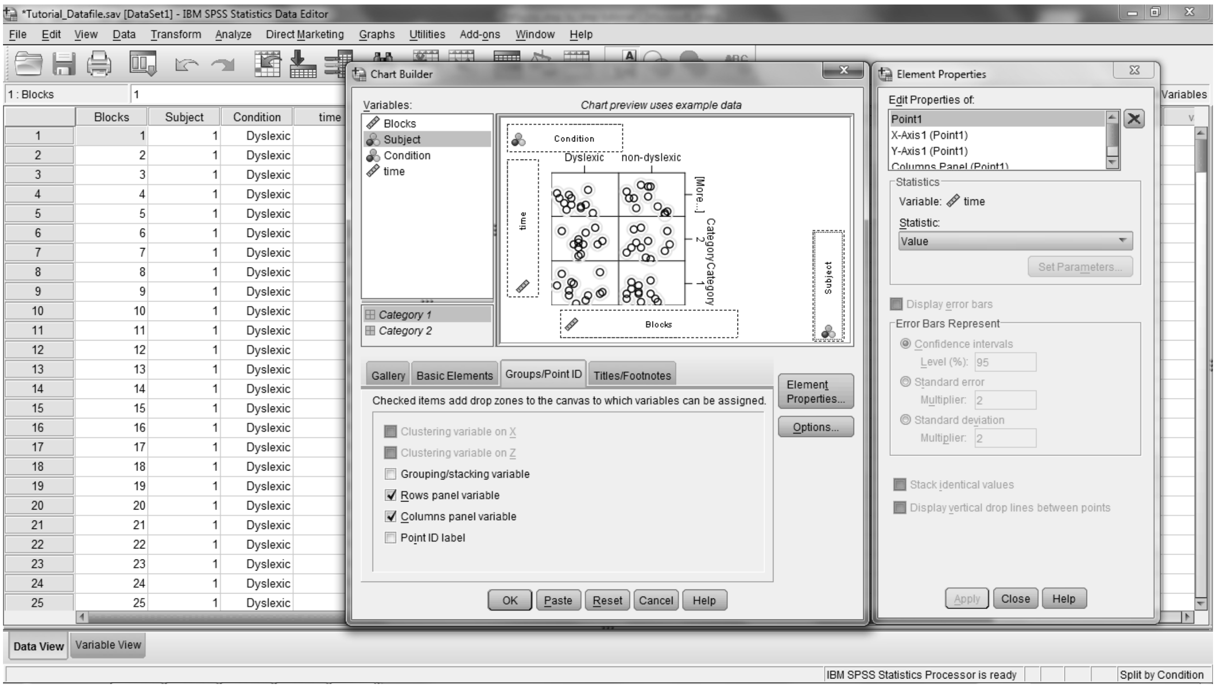
The output now contains two paneled charts which contain multiple scatter plots, one per participant. To improve the display of the learning effect it is possible to alter the size of the plots. By double clicking the output the chart editor pops up. By double clicking the chart editor it is possible to change the properties, including the chart size. In this case only the y axis display must be altered. To do this, deselect the Maintain aspect ratio, and then approximately double the height. This should provide an image similar to what is shown below.



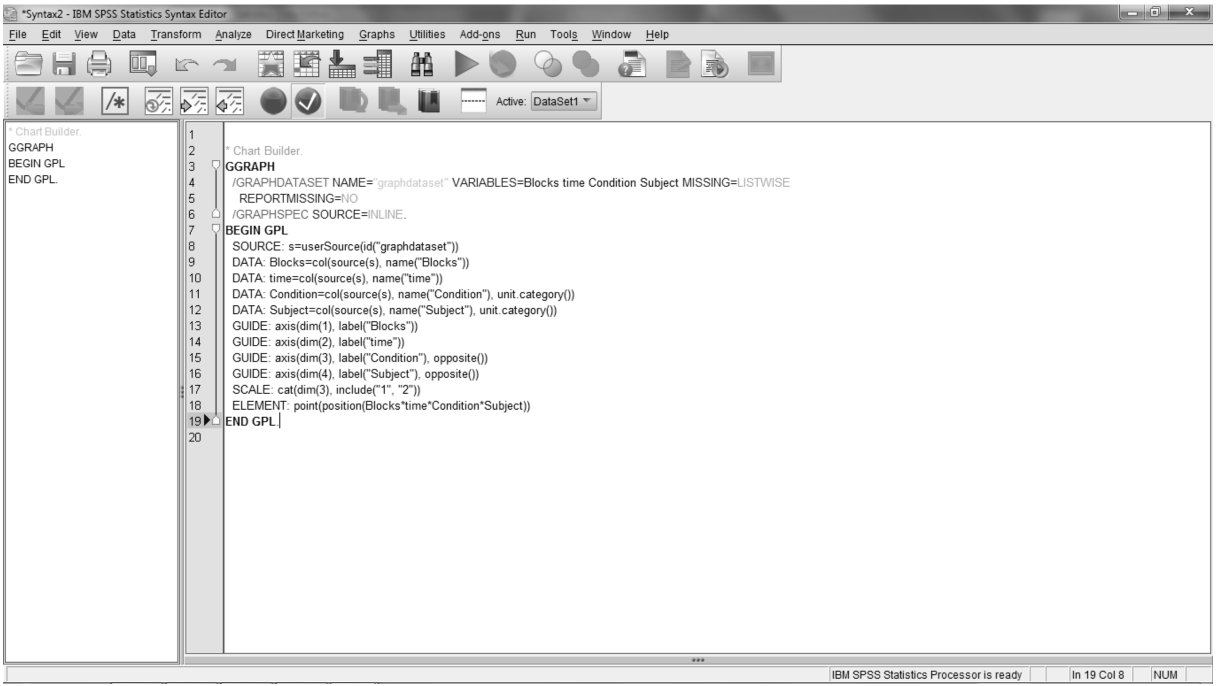
The trend in the data is now more easily recognized with the naked eye. The image can be further improved by adding a fit line. At this stage it is preferred to use a non parametric line because these have the least assumptions about the relationship between the dependent and independent variable (Jacoby, 2000). This means that nonparametric lines show the purest trend. In this case a Loess curve will be used (this function also contains a smoother). There are two ways to add these curves, one option is to use the build-in models within the chart editor, but the choice in models is limited. The other option is adding the fit line as an element in the syntax. The instructions on how to use the syntax are shown below.

*Step 4 : (Paneled chart in Chart builder) Adding a loess curve in the syntax*

Go to Graphs → this time click on Chart Builder…. → In the gallery select Scatter/Dot and double click on the option in the top left corner, this again is a simple scatter. Now drag the dependent variable (time) to the y-axis and the independent variable (Blocks) to the X-axis. Next click on Groups/Points ID and select both the Rows and Columns panel variable. These will appear in the chart preview, next drag the Subjects variable to the Rows and the Condition variable to the Columns. All filled in this should resemble the image below.



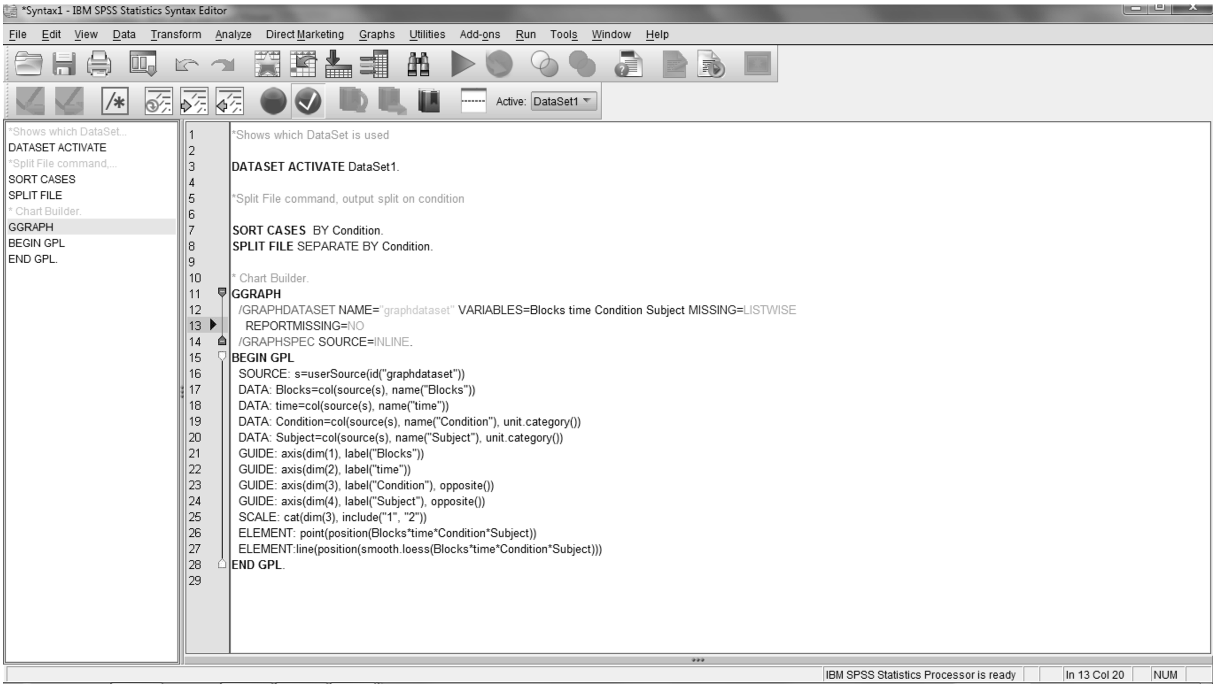
Now instead of pressing OK click on the Paste button. This will open a syntax file as is shown below.



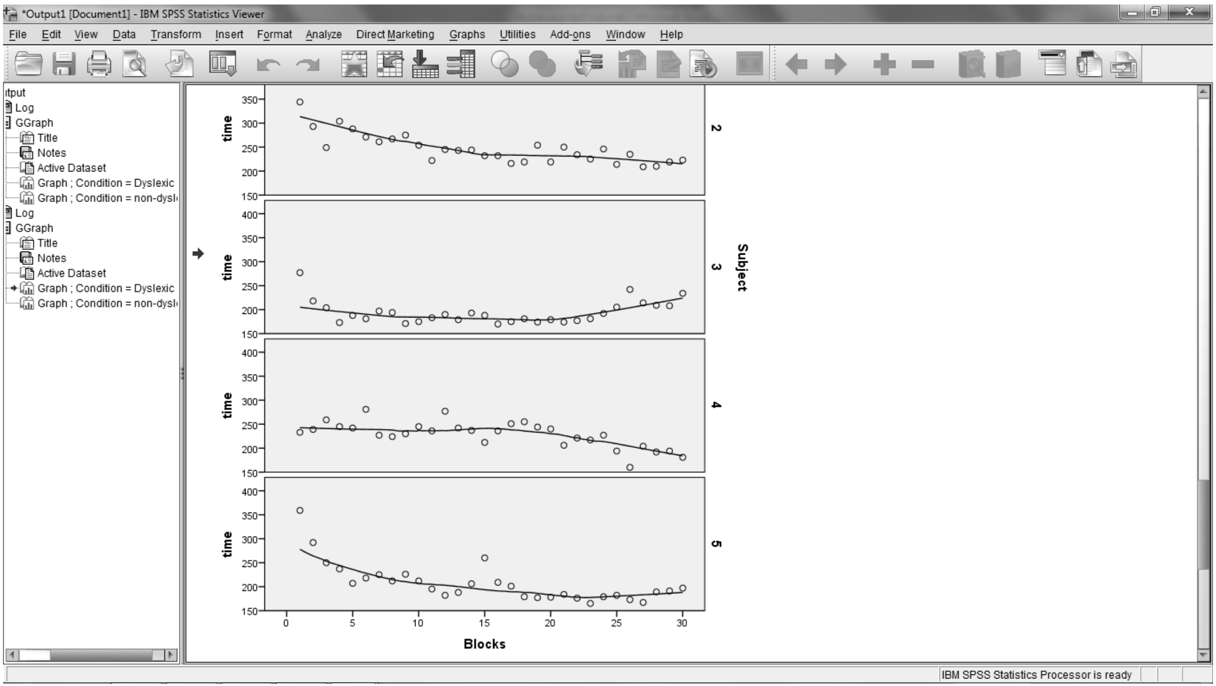

Remember that SPSS works from top to bottom, this is why the fit line must be entered at the end just above END GPL. There we create the loess curve as a new element:

ELEMENT:line(position(smooth.loess(Blocks*time*Condition*Subject)))

One last image which shows the syntax complete with the split file command and the added loess curve. In order to run the syntax select all the commands and click on the green triangle.



In the output we again go to (double click) → Chart editor (double click) → Properties and change the chart size in Height to approximately double its initial value. Now we can discuss the nonlinearity of the data.




As can be seen in the output image, the curvature is different for each subject. Subject 5 is a good example of a clear (nonlinear) learning curve, quite a steep start and a flattening of the curve approximately at block 20. This flattening is important for the asymptote but more on that in the next tutorial. The loess curve of subject 3 shows almost an opposite effect. The performance time is higher at the end than it was at the beginning of the training. Arguably the data could still be used up to Block 20. But this would be the choice of the researcher seeing as it depends on the topic and goal of the research. For further analysis it is wise to only pick subjects that show a learning trend. In this case subject 3 will not be used for further research because the cause of the distortion in the curve is unknown.

# Appendix B

## Tutorial 2: Model fitting

This is a step by step tutorial on how to perform a nonlinear regression analysis using IBM SPSS Statistics 20. This second tutorial compares two nonlinear regression models, both suited for analyzing learning. And it shows how to determine whether there is a significant difference in learning effects between two groups.

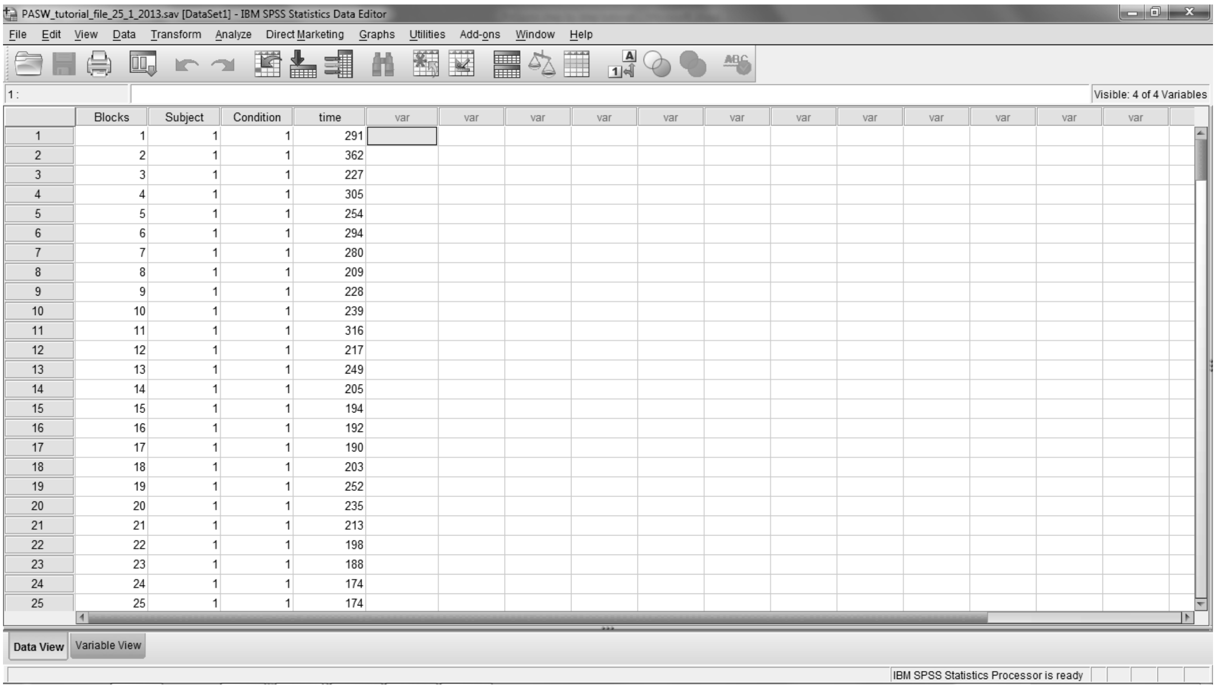
In learning curve plotting there is a choice between the linear and nonlinear regression model. Regression in general summarizes the dependence of one variable on another, for motor skill learning this is performance set against the time of practice. Where the linear model assumes a straight line relationship, a consistent change over time, the nonlinear model does not require this assumption (Draper & Smith, 1998). As is described in the swimming example in the introduction the development of motor skills shows a curved line that flattens out over time. This is consistent with the nonlinear regression model. This curvature is also found in the paneled charts of tutorial 1 (appendix A).

The first objective now is to fit a model per participant (except for subjects 3 and 7 who based on their scatter plots are not used in further analysis). The models that will be used are two asymptotic regression models

- Exponential model expression (b1 + b2 * exp(b3 * x) )
- Power model expression (b1 + b2 * b3 ** x)

The first step is to organize the data as is shown below. It shows the four initial variables Blocks (30 training sessions); Subjects (1 to 10); Condition (1=Dyslexic, 2=Non-dyslexic); time (performance time in seconds per block).

## *Step 1 : DataSet*

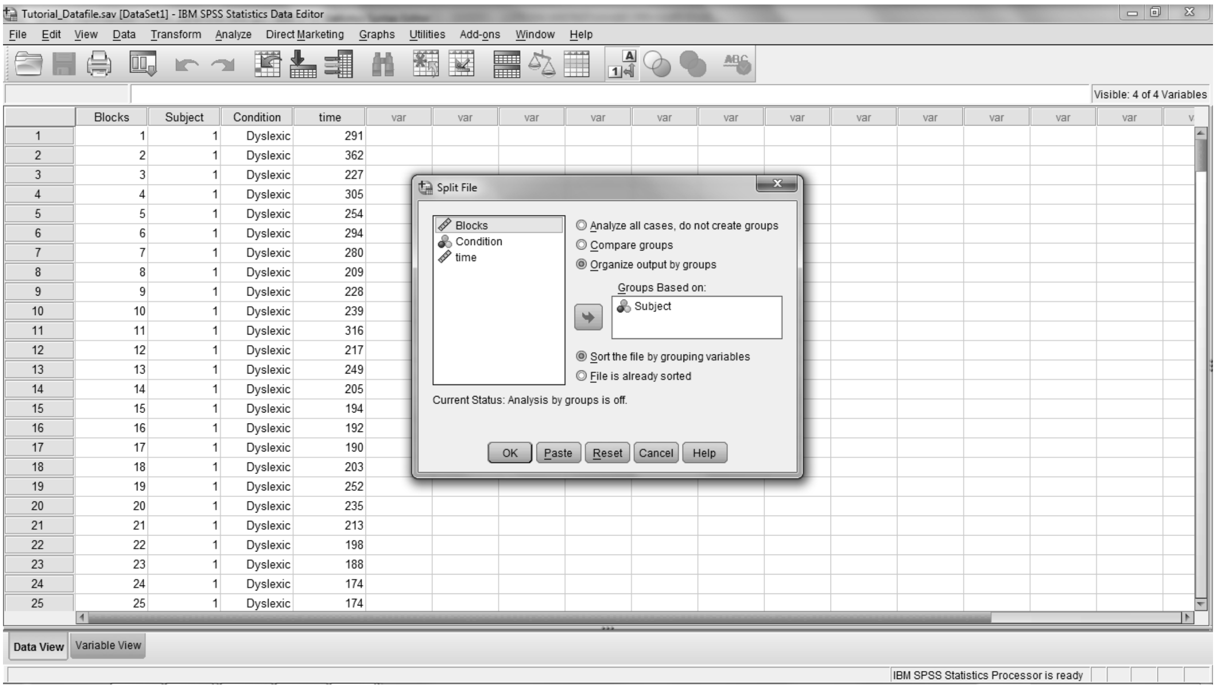


| | Blocks | Subject | Condition | time |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 291 |
| 2 | 2 | 1 | 1 | 362 |
| 3 | 3 | 1 | 1 | 227 |
| 4 | 4 | 1 | 1 | 305 |
| 5 | 5 | 1 | 1 | 254 |
| 6 | 6 | 1 | 1 | 294 |
| 7 | 7 | 1 | 1 | 280 |
| 8 | 8 | 1 | 1 | 209 |
| 9 | 9 | 1 | 1 | 228 |
| 10 | 10 | 1 | 1 | 239 |
| 11 | 11 | 1 | 1 | 316 |
| 12 | 12 | 1 | 1 | 217 |
| 13 | 13 | 1 | 1 | 249 |
| 14 | 14 | 1 | 1 | 205 |
| 15 | 15 | 1 | 1 | 194 |
| 16 | 16 | 1 | 1 | 192 |
| 17 | 17 | 1 | 1 | 190 |
| 18 | 18 | 1 | 1 | 203 |
| 19 | 19 | 1 | 1 | 252 |
| 20 | 20 | 1 | 1 | 235 |
| 21 | 21 | 1 | 1 | 213 |
| 22 | 22 | 1 | 1 | 198 |
| 23 | 23 | 1 | 1 | 188 |
| 24 | 24 | 1 | 1 | 174 |
| 25 | 25 | 1 | 1 | 174 |

*Step 2: Split file*

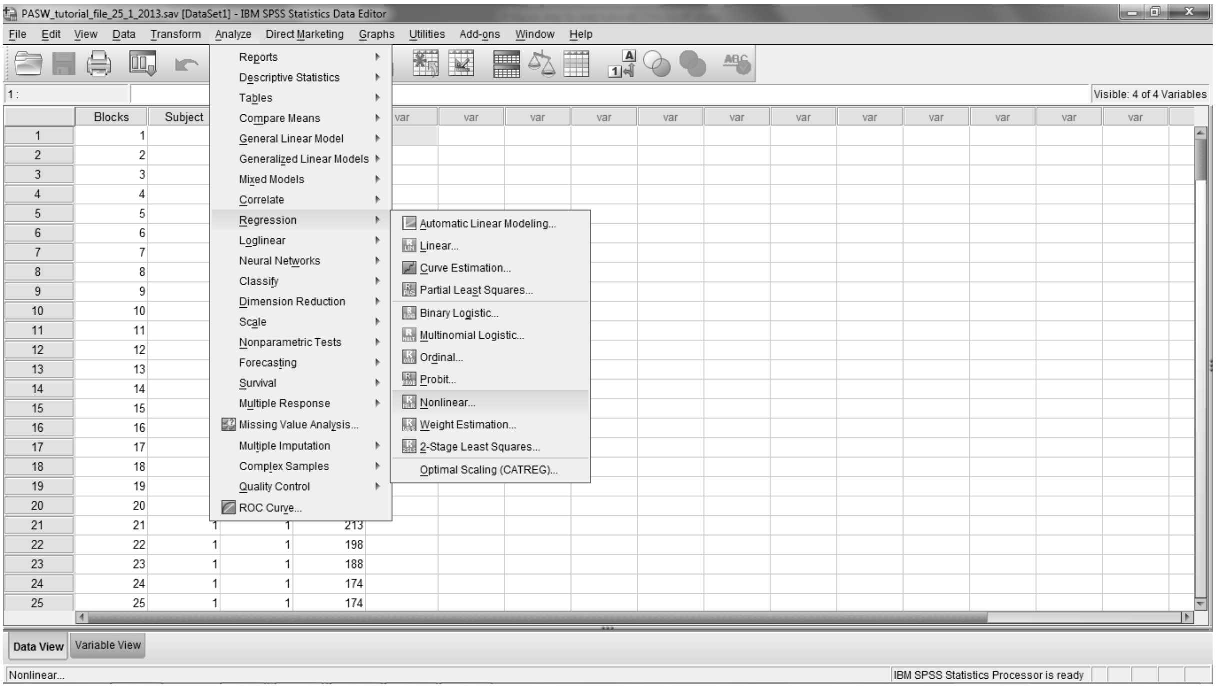
Now it is necessary to split the file output on subject. Doing this allows us to determine the fit of each model for each participant. If you have followed the previous tutorial keep in mind that the previous split file command might still be active.

The Split File command: Data → Split File… In the pop-up screen select the options Organize output by groups and Sort the file by grouping variables. Enter the Subject variable as the Groups based on: as is shown below. Before clicking OK click on Paste to put the command in a syntax file, this will be used later. Now click OK.



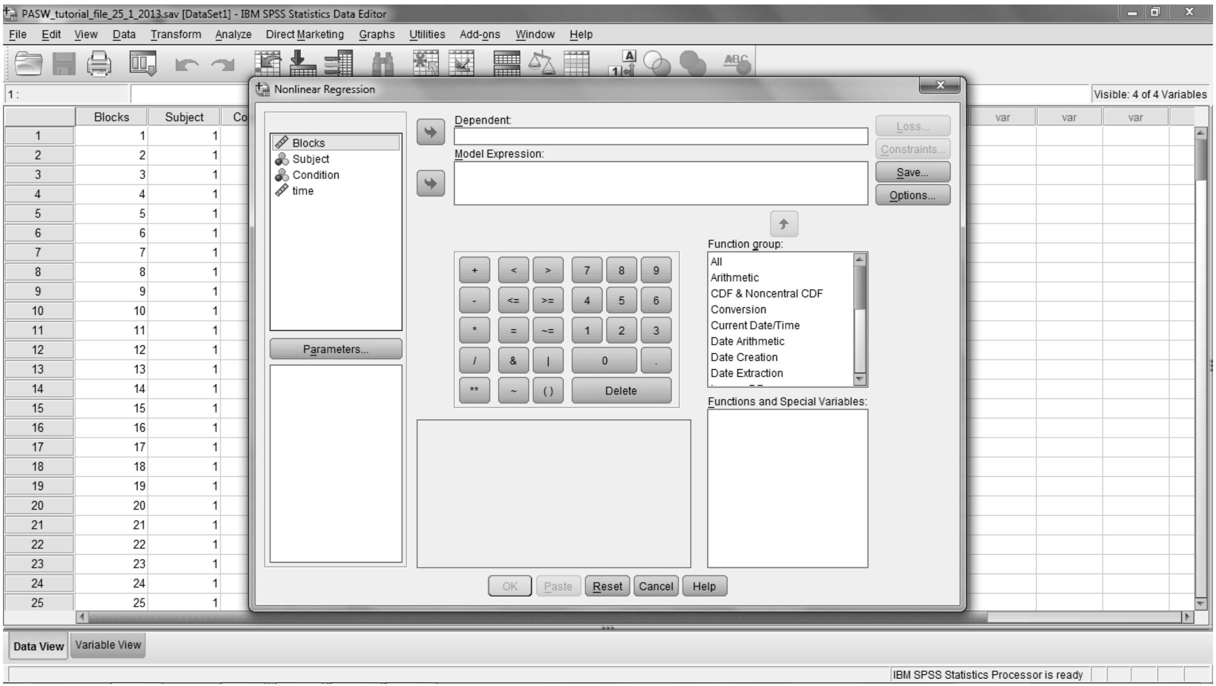
*Step 3: Regression → Nonlinear*

In order to get to the pop-up screen where we can perform nonlinear regression click on



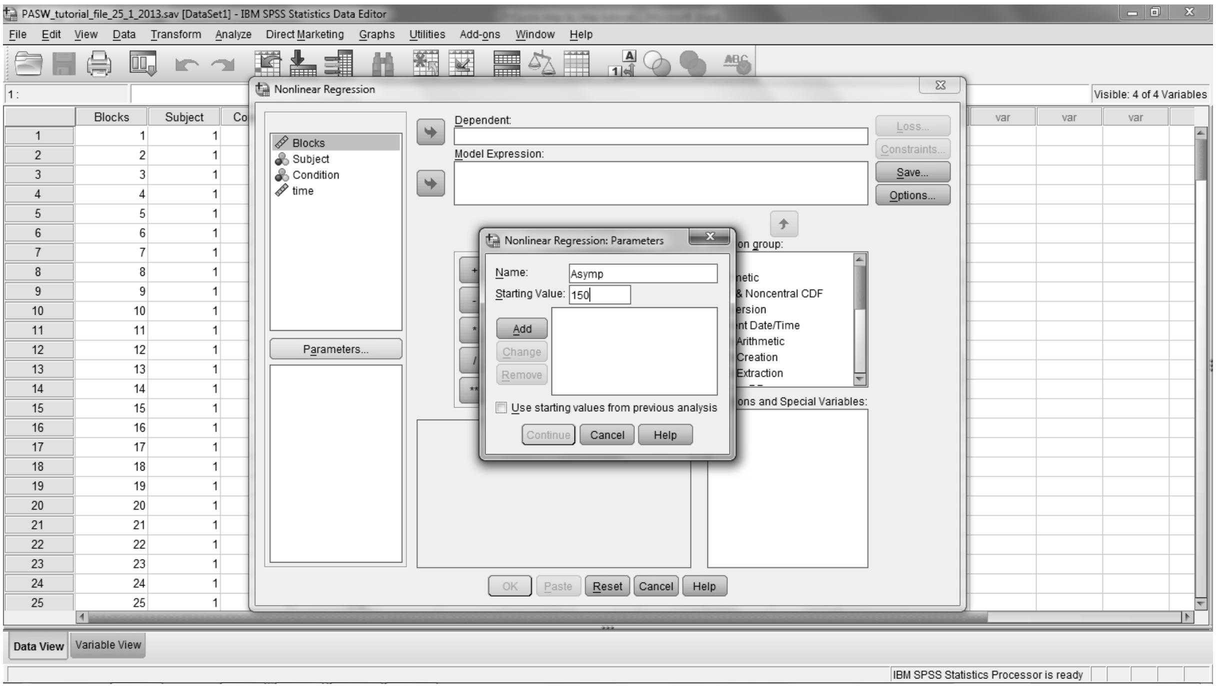

Analyze → Regression → Nonlinear..

In order to perform nonlinear regression the parameters (b1, b2 and b3) must be declared and given starting values. This can be done when click on Parameters… this opens a new and smaller pop-up screen.

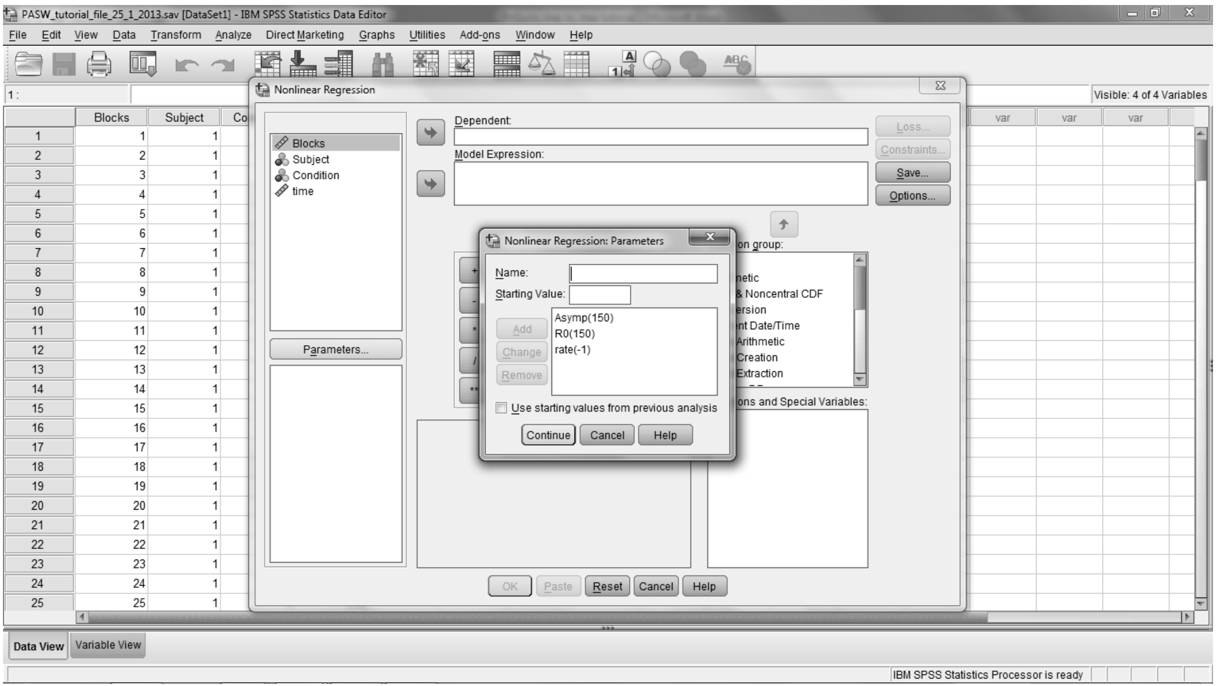


*Step 4: Declaring the parameters (b1, b2 and b3)*

Enter the name you wish to use for your first parameter (b1), in this case Asymp. And provide it with a starting value, remember to choose these starting values wisely. Next click on the Add button and repeat this for your other parameters (b2 and b3) R0 and rate. The starting values are important because SPSS will start with these values and through small steps (iteration) will search for the optimal values for your parameters. Only when these optimal values are found will there be convergence.

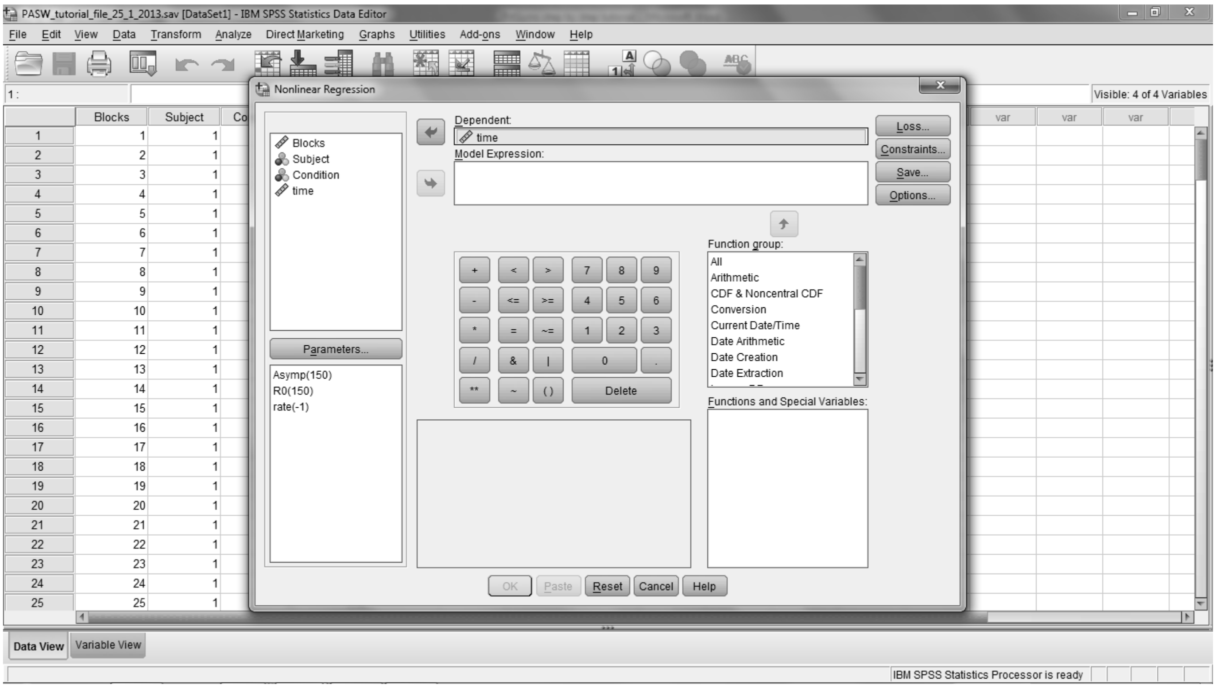



Now that all parameters are given their names and values, click on continue.



*Step 5: enter the model expression*

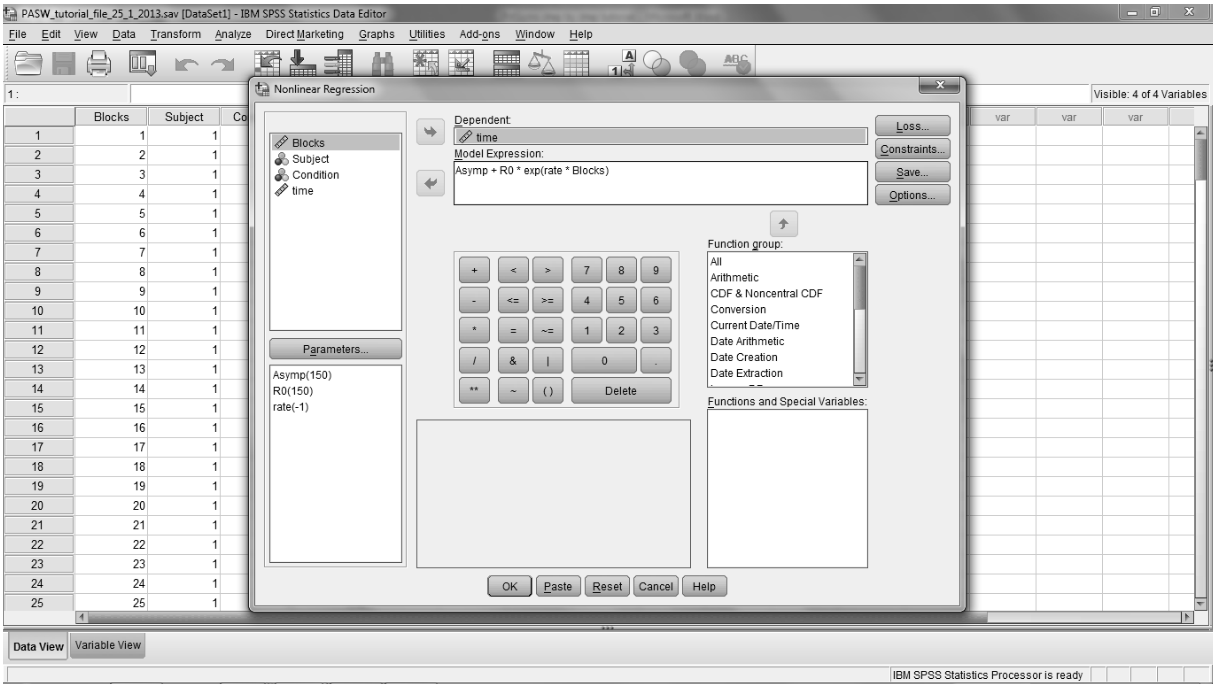
First of all select the variable time and place it as the dependant variable. (As you can see the



new parameters are displayed in the left lower corner).

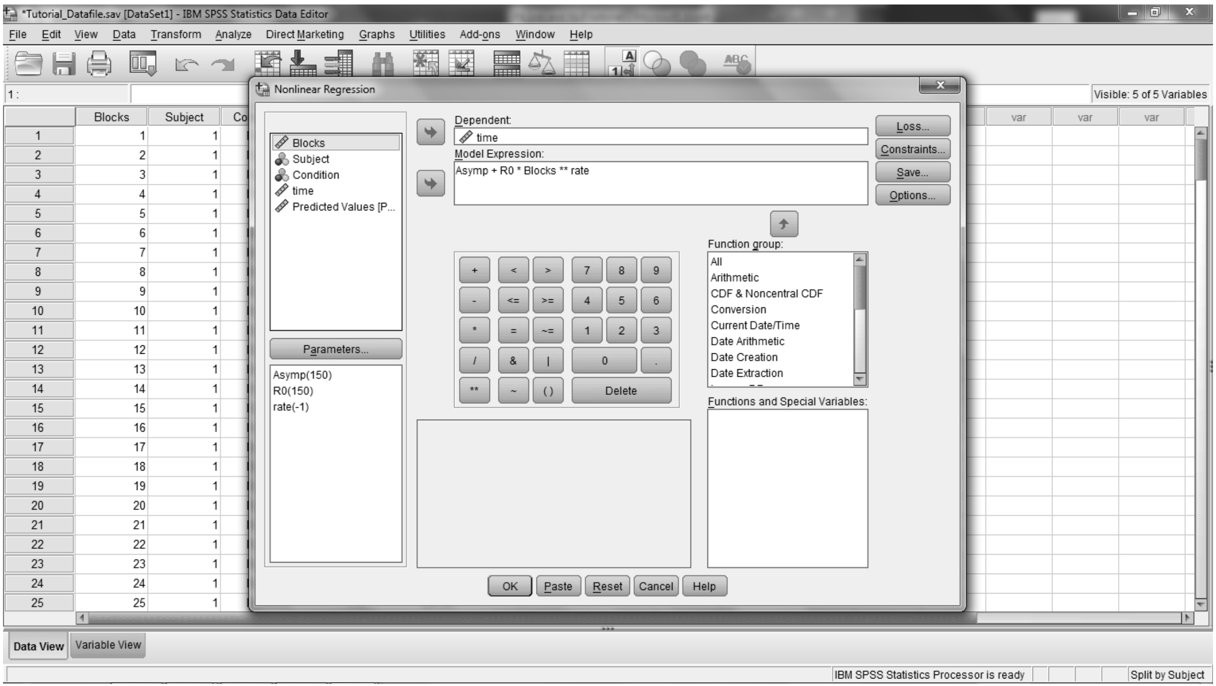
Next we enter the formula (in this case the exponential model) as the Model Expression: Asymp + R0 * exp(rate*Blocks). Again click on Paste to add this nonlinear command to the syntax file.

Do not click OK!



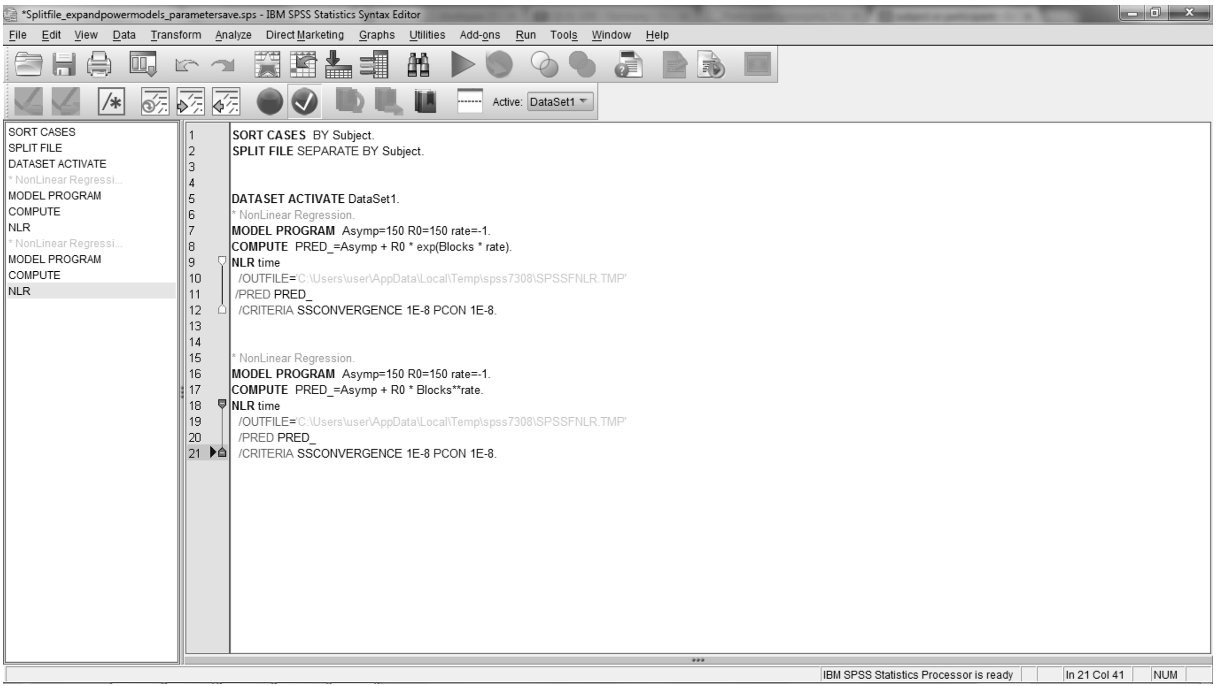
*Step 6: Enter the second model*

Now enter the other model (Asymp + R0 * Blocks ** rate) and again click on Paste. Now the



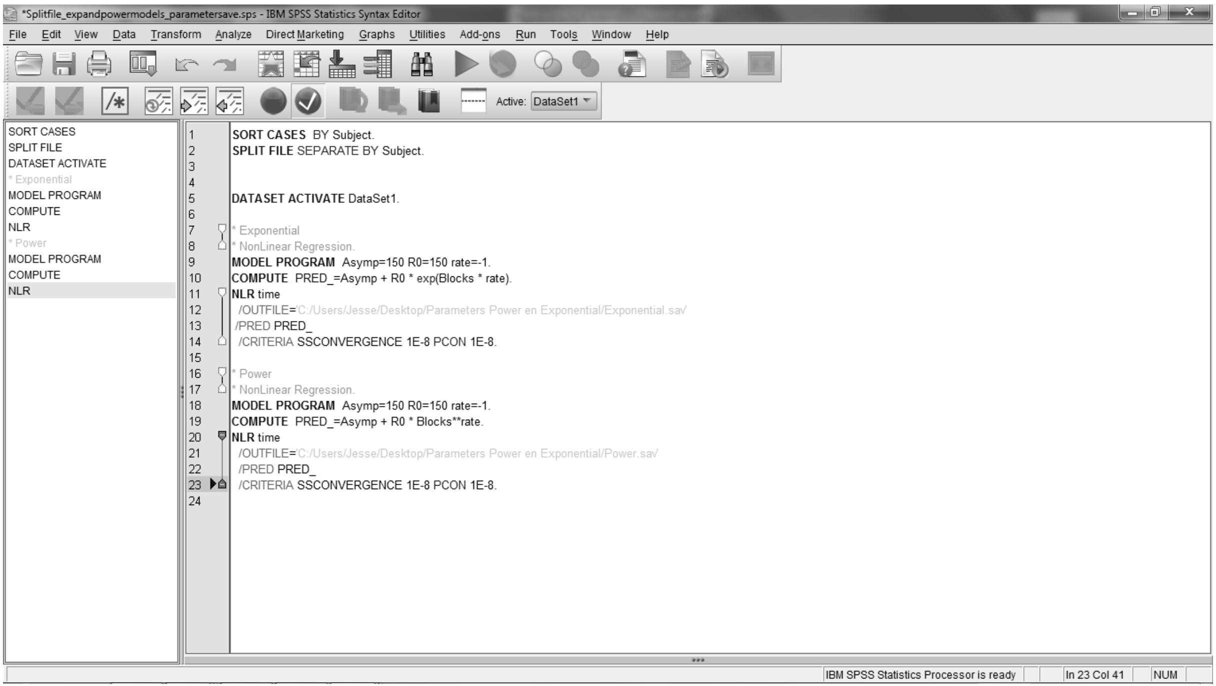

pop-up screen can be closed.

The syntax file should contain the same commands as are shown below.



*Step 7: Saving parameters*

Before examining which model fits which subject best, it is best to create a little structure in the output files. It is possible to save the final parameter estimates to a .sav file for further analysis. In order to do this we must change the destination of the OUTFILE. There are two things that one has to keep in mind, first to use the slash symbol / instead of the backslash symbol \ when saving to a permanent file. Second, to save parameters to a data file .tmp must be changed into .sav format. Also it is advisable to use two destinations, one per model. An example is shown below.



*Step 8: Analysis*

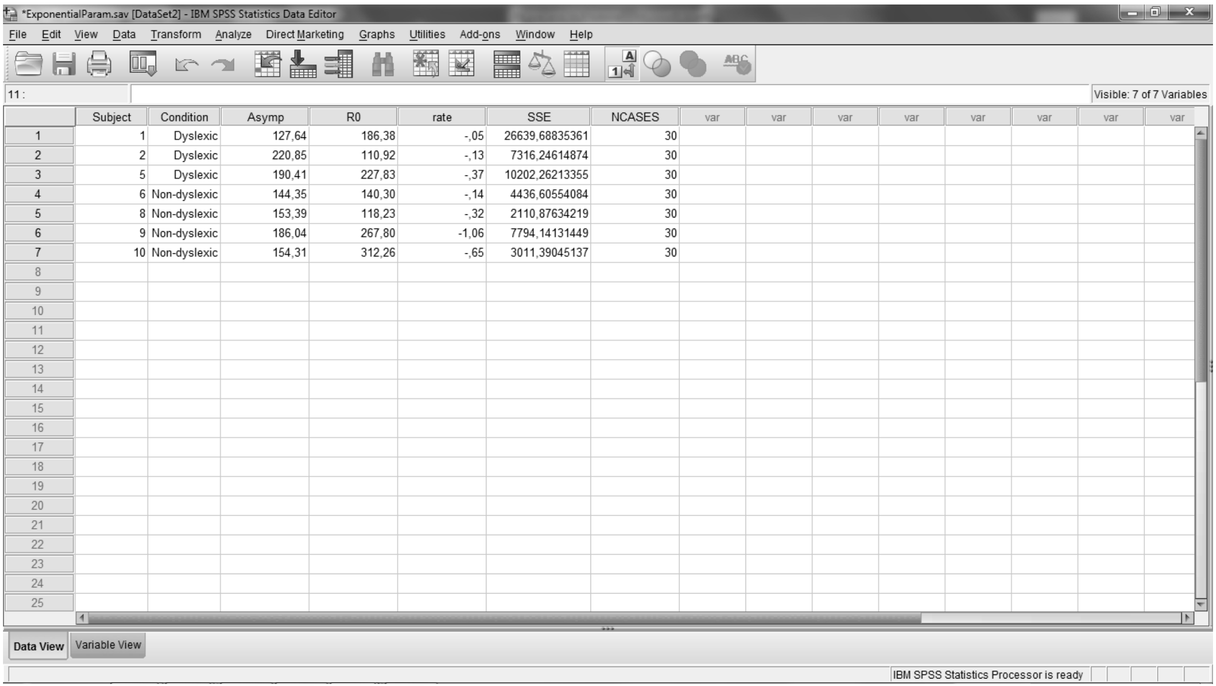
To run the syntax file, select all the commands and click on the green triangle. Now the final parameter data files have been constructed. However we must first determine which model fits best with which subject. To determine how well a model fits a subject look at the R-squared values in the output file. For a better view on the results it is advisable to place all the R-squared values in a single table (excel).

| Subject | | R-squared | Convergence |
|---|---|---|---|
| 1 | Power | 0,595 | Limit |
| | Exponential | 0,629 | SSCON |
| 2 | Power | 0,761 | SSCON |
| | Exponential | 0,741 | SSCON |
| 4 | Power | 0,255 | Limit |
| | Exponential | 0,469 | Limit |
| 5 | Power | 0,834 | SSCON |
| | Exponential | 0,790 | SSCON |
| 6 | Power | 0,912 | SSCON |
| | Exponential | 0,881 | SSCON |
| 8 | Power | 0,890 | SSCON |
| | Exponential | 0,855 | SSCON |
| 9 | Power | 0,587 | SSCON |
| | Exponential | 0,541 | SSCON |
| 10 | Power | 0,930 | SSCON |
| | Exponential | 0,916 | SSCON |

The R-squared values give an indication of the amount of variance in the data that is explained by the model. In the convergence column SSCON means that the sum of squares for the parameters have converged to the mode and Limit means that the amount of iterations has reached its limit before convergence could occur. For the cases in which the models have converged the power model shows a slightly higher R-squared value. This is however such a small difference that it cannot be stated that one of the models out performs the other. However seeing as for subject 1 the exponential model gives an extra convergence to the model this model will be used for further analysis. As no convergence has occurred in the case of subject 4 the final parameters, which are found through iteration, of this participant are useless for further analysis. The data from subject 4 will for this reason be discarded.

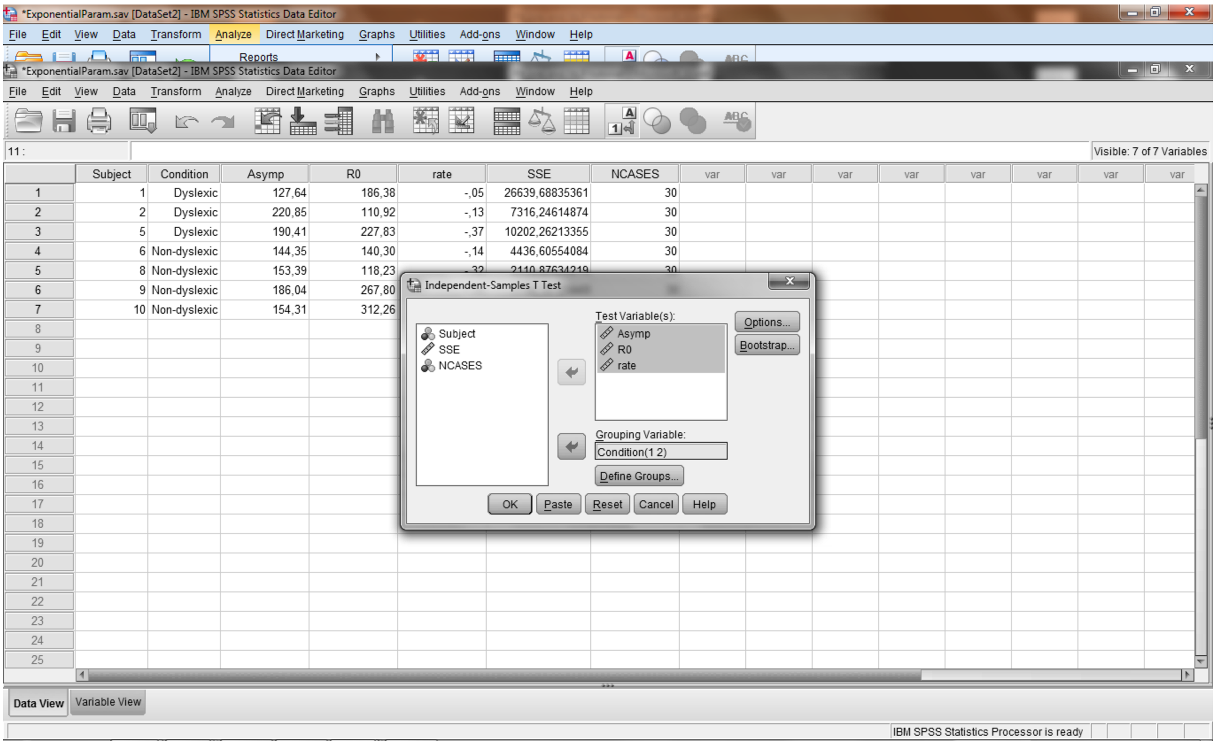
*Step 9: comparing the parameters*

Now open the exponential parameter file from step 6. This should look similar to the file below. Seeing as this is a new file the condition variable must be added again (And due to lack of convergence to the model subject 4 is removed from the data file).



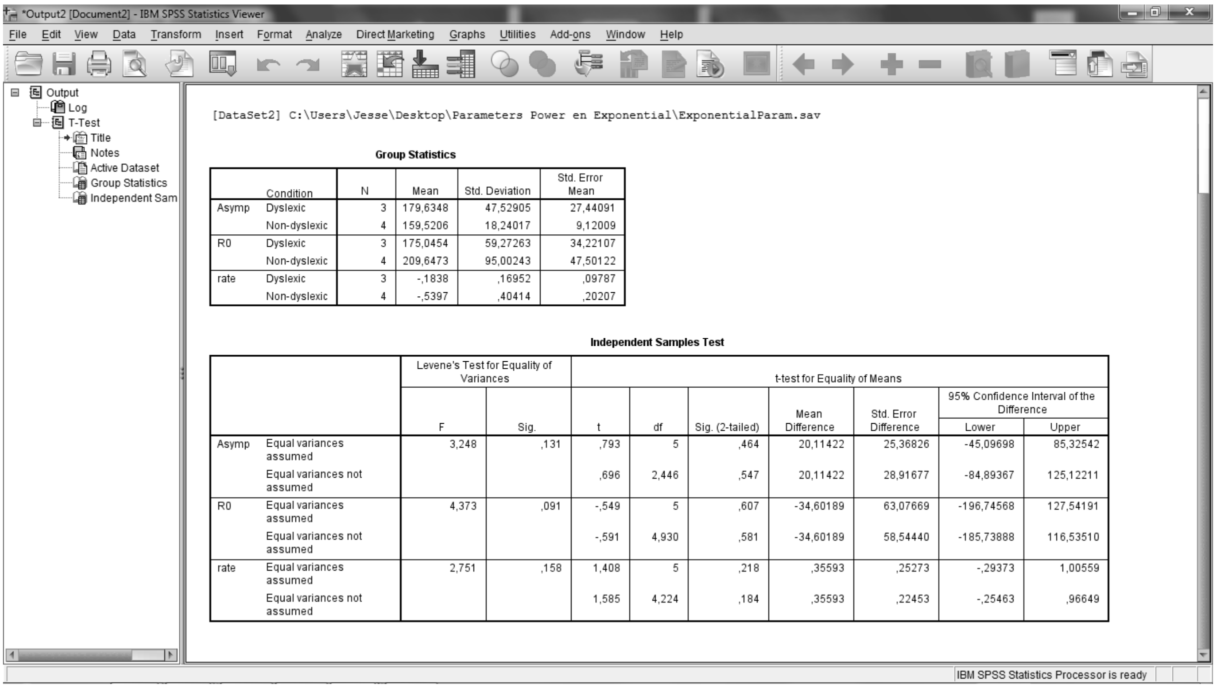
| | Subject | Condition | Asymp | R0 | rate | SSE | NCASES |
|---|---|---|---|---|---|---|---|
| 1 | 1 | Dyslexic | 127,64 | 186,38 | -,05 | 26639,68835361 | 30 |
| 2 | 2 | Dyslexic | 220,85 | 110,92 | -,13 | 7316,24614874 | 30 |
| 3 | 5 | Dyslexic | 190,41 | 227,83 | -,37 | 10202,26213355 | 30 |
| 4 | 6 | Non-dyslexic | 144,35 | 140,30 | -,14 | 4436,60554084 | 30 |
| 5 | 8 | Non-dyslexic | 153,39 | 118,23 | -,32 | 2110,87634219 | 30 |
| 6 | 9 | Non-dyslexic | 186,04 | 267,80 | -1,06 | 7794,14131449 | 30 |
| 7 | 10 | Non-dyslexic | 154,31 | 312,26 | -,65 | 3011,39045137 | 30 |

In order to compare the parameters of the two groups (Dyslexic and Non-dyslexic) an independent samples t-test will be used, with Condition as the between-subjects factor. Click on Analyze → Compare Means → Independent-Samples T test...




In the pop-up screen place the three parameters (Asymp, R0 and rate) as the Test Variable(s): and select and define Condition as the Grouping variable: and click on OK.

Seeing as the significance levels for the Levene's test are all higher than .05 the t-values for equal variances assumed will be used. The output file shows that there are no significant



[DataSet2] C:\Users\Jesse\Desktop\Parameters Power en Exponential\ExponentialParam.sav

**Group Statistics**

| | Condition | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Asymp | Dyslexic | 3 | 179,6348 | 47,52905 | 27,44091 |
| | Non-dyslexic | 4 | 159,5206 | 18,24017 | 9,12009 |
| R0 | Dyslexic | 3 | 175,0454 | 59,27263 | 34,22107 |
| | Non-dyslexic | 4 | 209,6473 | 95,00243 | 47,50122 |
| rate | Dyslexic | 3 | -,1838 | ,16952 | ,09787 |
| | Non-dyslexic | 4 | -,5397 | ,40414 | ,20207 |

**Independent Samples Test**

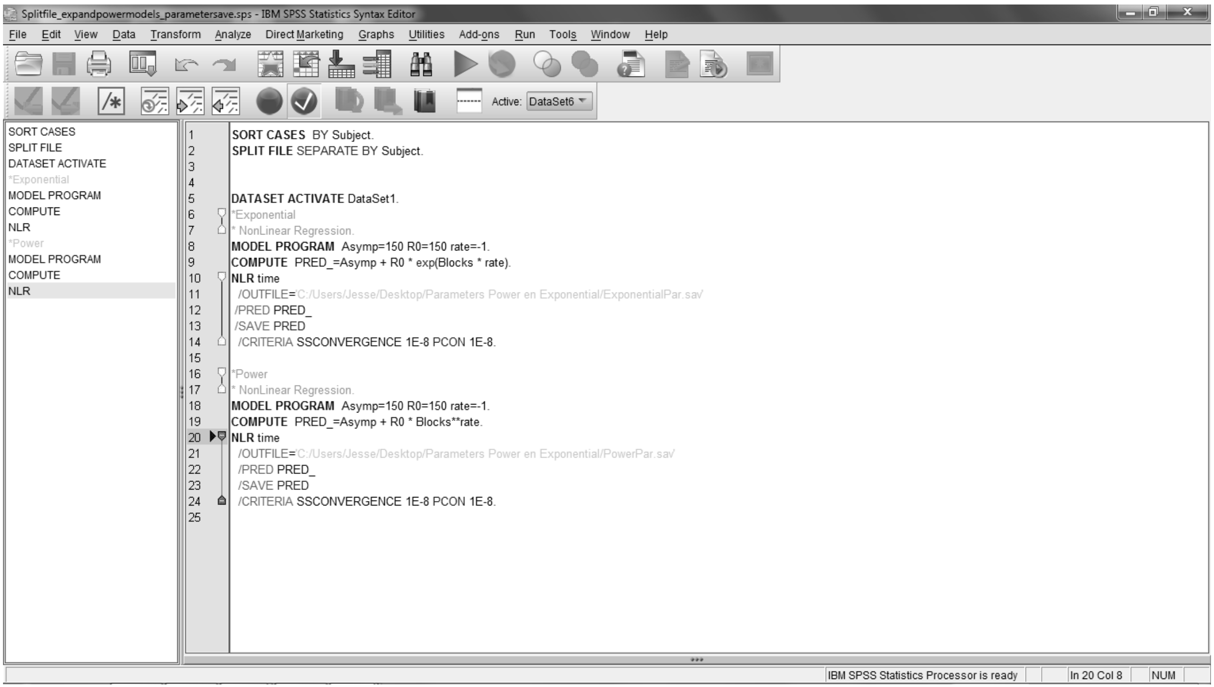
| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| Asymp | Equal variances assumed | 3,248 | ,131 | ,793 | 5 | ,464 | 20,11422 | 25,36826 | -45,09698 | 85,32542 |
| | Equal variances not assumed | | | ,696 | 2,446 | ,547 | 20,11422 | 28,91677 | -84,89367 | 125,12211 |
| R0 | Equal variances assumed | 4,373 | ,091 | -,549 | 5 | ,607 | -34,60189 | 63,07669 | -196,74568 | 127,54191 |
| | Equal variances not assumed | | | -,591 | 4,930 | ,581 | -34,60189 | 58,54440 | -185,73888 | 116,53510 |
| rate | Equal variances assumed | 2,751 | ,158 | 1,408 | 5 | ,218 | ,35593 | ,25273 | -,29373 | 1,00559 |
| | Equal variances not assumed | | | 1,585 | 4,224 | ,184 | ,35593 | ,22453 | -,25463 | ,96649 |

differences between the groups. This is clear for both the significance levels and the corresponding confidence intervals.

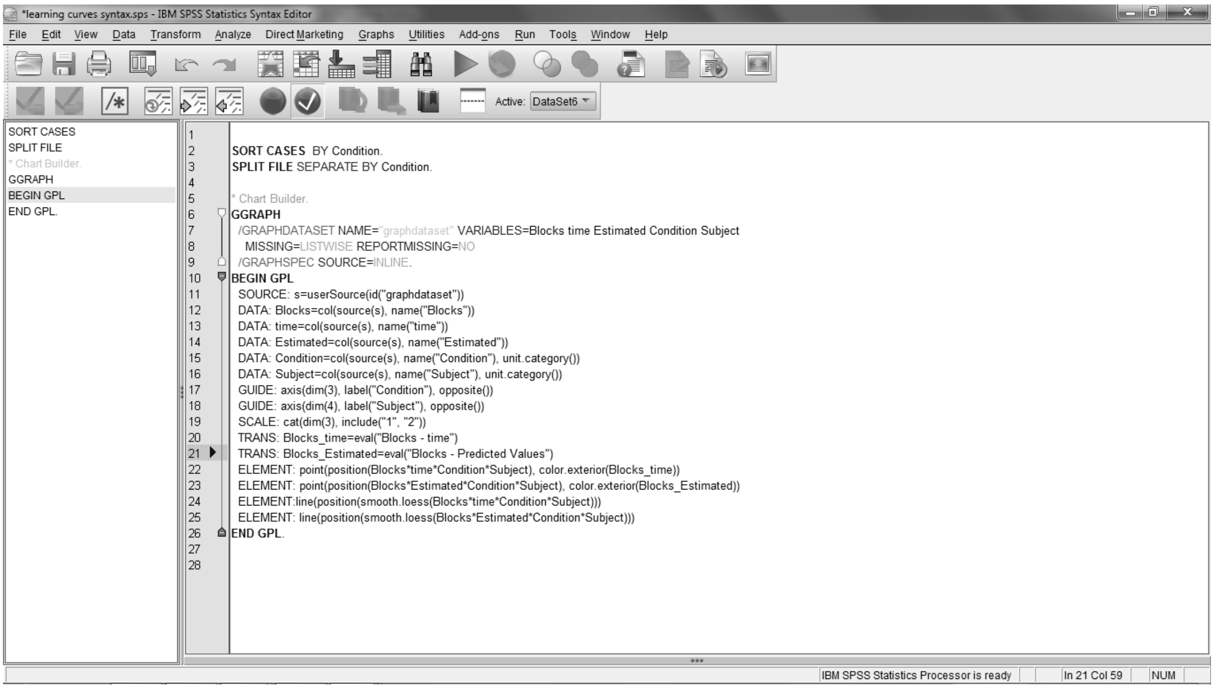
# Appendix C

## Syntax commands for nonlinear modeling and analysis

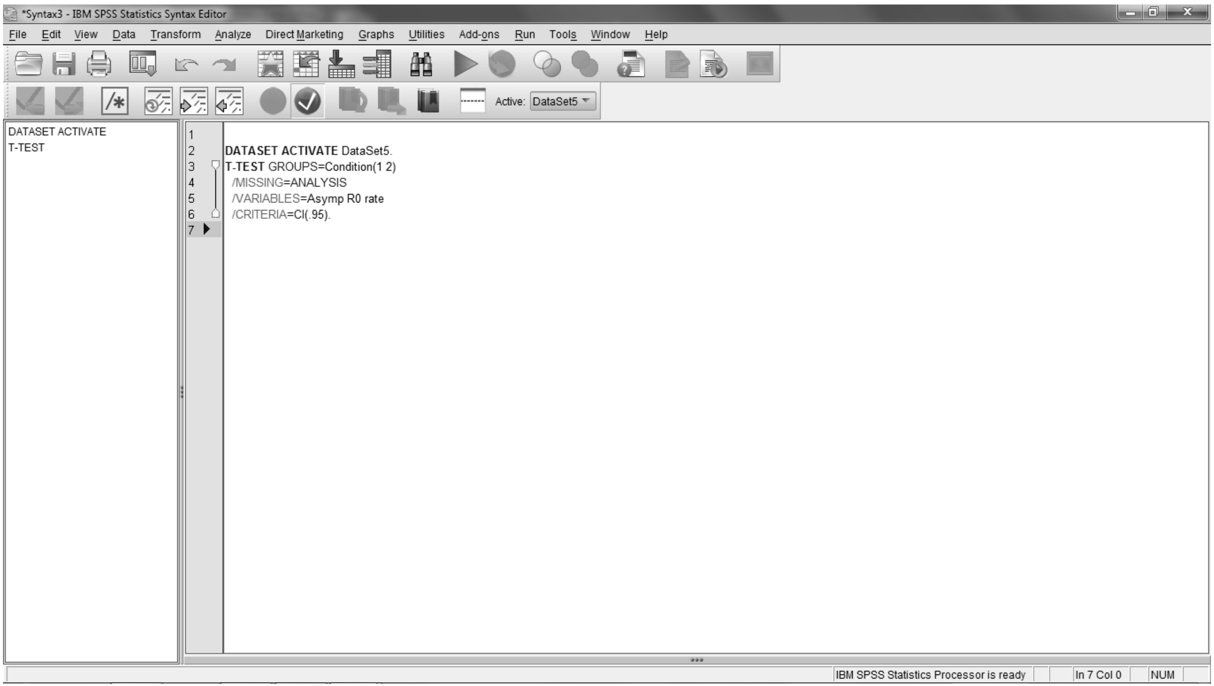
This first window shows the commands for splitting the output per participant. The modeling commands for both nonlinear regression models (exponential and power). The save command to save predicted values for both models to the original data file. Furthermore the out file destinations have been changed to save the final parameters to new data files.



The print screen below shows the commands for creating two paneled charts, one for each condition, which contain a scatter plot per participant. The last two elements create two loess curves, one for the estimated values which were saved by the commands in the previous window and one for the measured values from the experiment.




This third window shows the command for comparing the mean parameter values with condition (dyslexic and non-dyslexic) as the between subjects factor. This is done by using the new data files (in this case the exponential file) for the final parameter estimations, which were created by the commands in the first syntax window.



Appendix D

Dutch instructions as used in the experiment

Allereerst hartelijk dank voor je deelname aan dit onderzoek. Zo direct mag je het formulier wat voor je is klaargelegd omdraaien. Op dit formulier staan 10 zinnen. Het is de bedoeling dat je deze zinnen gaat invoeren op de computer. Dit invoeren op de computer is afgeleid van hoe men dit met de Swype functie op een Samsung smartphone zou doen.

Voor mensen die niet bekend zijn met Slide-it staat hieronder een korte uitleg en een plaatje. Het is de bedoeling dat je voor elk woord de cursor/muispijl op de eerste letter plaatst en vervolgens de linkermuisknop indrukt, deze blijf je inhouden terwijl je de cursor/muispijl over de overige letters van het woord beweegt. Op basis van jouw bewegingen zal het programma woord suggesties geven. Als het woord wat jij wilt typen de eerste suggestie is, kun je gewoon doorgaan met invoeren van het volgende woord, het programma zal voor jou de spatie plaatsen. Om te kijken of je het begrepen hebt kun je de volgende zin invoeren:


- Jan is heel erg moe -

Indien je vragen hebt over de invoeringsmethode kun je die nu aan de begeleider stellen.

Dit onderzoek is opgezet in twee gelijke delen, gescheiden door een pauze van 30 minuten. Ieder deel bestaat uit 15 blokken en per blok zal je gevraagd worden om 10 zinnen in te voeren met de hierboven beschreven methode.

Nog een aantal aandachtspunten en dan zijn we klaar om te beginnen.

1. Probeer de zinnen zo snel mogelijk in te voeren
2. Ga bij fouten niet de zin verbeteren maar door met de volgende zin
3. Klik aan het eind van elke zin op enter om met de volgende zin op een nieuwe regel te beginnen
4. De leestekens (komma’s, punten en vraagtekens) hoef je niet in te voeren

Heel veel succes gewenst en je mag nu het blad omdraaien en beginnen!!

## Appendix E

### German instructions as used in the experiment

Zuerst möchte ich mich vielmals bei dir für deine Teilnahme an dieser Untersuchung bedanken.

Gleich darfst du das Formular, das vor dir bereit liegt, umdrehen. Auf diesem Formular stehen 10 Sätze. Das Ziel ist, dass du diese Sätze in den Computer einfügst. Dieses Einfügen ist hergeleitet von der Swype Funktion des Samsung Smartphones und macht die Arbeit auf dem Computer möglich.

Für diejenigen, die Slide-it nicht kennen, steht eine kurze Erklärung mit einem Bild zur Verfügung. Die Aufgabe ist, dass du vor <u>jedem Wort</u> den Cursor/Mauspfeil auf den ersten Buchstaben setzt und anschließend den linken Mausknopf drückst. Diesen musst du gedrückt halten während du den Cursor/Mauspfeil über die übrigen Buchstaben des Wortes bewegst. Auf Grund deiner Bewegungen wird das Programm Wortvorschläge angeben. Wenn das Wort, das du eintippen willst, der erste Vorschlag ist, kannst du ganz normal mit dem Einfügen des nächsten Wortes weitermachen. Das Programm wird für dich die Lehrzeichen setzten. Um zu sehen, ob du es verstanden hast kannst du die nächsten Sätze einfügen:

-Jan ist sehr müde-


Falls du Fragen über die Einführungsmethode hast, kannst du diese nun an deinen Begleiter stellen. Diese Untersuchung ist in zwei gleiche Arbeitsabschnitte eingeteilt, getrennt durch eine 30 minütige Pause. Jeder Abschnitt besteht aus 15 Blöcken. Pro Block musst du 10 Sätze mit der oben beschriebenen Methode einsetzen.

Hier noch ein paar Hinweise, dann kannst du beginnen.

1. Probiere die Sätze so schnell wie möglich einzufügen.
2. Die Fehler nicht verbessern, sondern mit dem nächsten Satz fortfahren.
3. Klick am Ende jeden Satzes auf Enter, um den nächsten Satz auf einer neuen Zeile beginnen zu können.
4. Die Zeichensetzung (Komma, Punkt und Fragezeichen) brauchst du nicht

   einzufügen.Viel Erfolg! Du darfst nun das Blatt umdrehen und beginnen!!

# Appendix F

## Dutch sentences sheet

Hieronder staan de 10 zinnen vermeld. Gelieve deze in de juiste volgorde in te voeren.

Veel succes!!

1. Peter, hoe gaat het met jou?
2. Het is goed weer voor een feest.
3. Het is vroeg zomer dit jaar.
4. Wij gaan straks koffie drinken.
5. Ik heb mijn verslag bijna klaar.
6. We eten straks samen een broodje.
7. Hoe is je toets gegaan?
8. Alvast een goede reis gewenst.
9. Heb je Klaas al dag gezegd?
10. Er is onweer op komst.

# Appendix G

## German sentences sheet

Hier sind die 10 Sätze. Füge diese bitte in derselben Reihenfolge ein.

Viel Erfolg!!

1. Peter, wie geht es dir?
2. Es ist gutes Wetter für ein Fest.
3. Es ist früh Sommer dieses Jahr.
4. Wir gehen gleich Kaffee trinken.
5. Ich habe den Aufsatz fast fertig.
6. Wir essen gleich einen Kuchen.
7. Wie war dein Test?
8. Schon mal eine gute Reise.
9. Hast du Klaus schon hallo gesagt?
10. Es läuft auf regen hinaus.