**Introduction**

In this student placement dataset, an investigation is conducted upon request from an organisation’s marketing department. The aim of this investigation is to identify potential hidden problems or interesting relationships between different factors that determines campus placement among students.

The end result of this investigate should not only answer the following proposed questions; but also provide meaningful insights that lead the marketing department to execute informed decision making:

1. What are the academic factors that affect campus placement among students?
2. What are the factors that affect academic performance?
3. Does a student’s family background affect his/her academic performance?
4. What are the factors that affect salary?
5. What are the factors that affect students’ employability?

**Data Import**

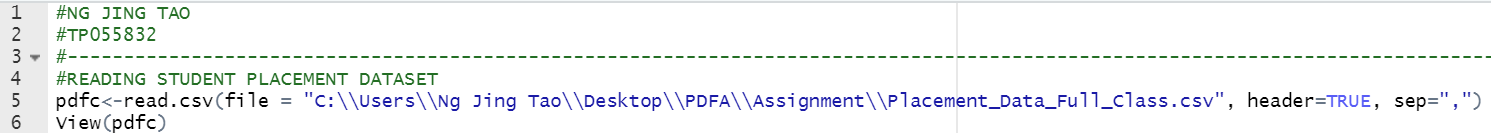
****

Figure 1: Import student placement dataset

The generated data frame containing data from the student placement dataset which is read from the provided file path with the help of built-in *read.csv()* function is assigned to variable *pdfc*. Header parameter in the *read.csv()* function is set to TRUE to return first row of values in dataset as column names while *sep* parameter is set to value of “*,*” due to the dataset is stored as a comma-separated values file with comma as its default delimiter (Software Carpentry, 2022). The *View()* function is used to perform simple EDA (exploratory data analysis) to improve understanding of data in this dataset (McPherson, 2021).

**Data Cleaning**

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Description automatically generated**

Figure 2: Check for missing data

Before performing data cleaning, the *summary()* function is used to provide brief statistical information rundown of all columns in the dataset to check for any missing values. The returned result is that only a *salary* column contains 8265 missing numerical values. On the other hand, there are no missing categorical values as checked by the *length()* and *is.na()* functions. The *is.na()* function is used to check for missing values in the above categorical dataset columns, and the output is determined by the return value of *TRUE* or *FALSE*.

Diagram

Description automatically generated with low confidence

Figure 3: Missing numerical values in Salary column

**Data Preprocessing**

**Text

Description automatically generated**

Figure 4: Handling missing values

Missing values in the *salary* column is replaced with its mean value using the *mean()* function. The *round()* function is also used to round off values of *salary* column to 0 decimal place to enable better data visibility (Geeks for Geeks, 2022). Afterwards, the *table()* function is called to display frequency of existing NA values to ensure all missing values are successfully replaced (DataScienceMadeSimple, 2022).

**Text

Description automatically generated**

Figure 5: After replacing missing salary values

**Text

Description automatically generated**

Figure 6: Round up values in numerical columns

All values in categorical columns such as *ssc\_p*, *hsc\_p*, *degree\_p* and *etest\_p* are all round off to a value of 0 to ensure data consistency. This is because some rows consist numerical values of 0, 1 or 2 decimal places.

**Data Transformation**

**Table

Description automatically generated**

Figure 7: Rename and add new columns to dataset

All existing dataset column names are assigned with new names of capitalised version to differentiate the changes made in renaming process. The *mutate()* function from the “*dplyr*” package is used to add cleaned and preprocessed columns into the dataset as new columns. In the meantime, unchanged columns will be renamed with the *rename()* function with their values unchanged in the dataset. The *colnames()* function is used to differentiate the before and after dataset column renaming process.

**A close-up of a document

Description automatically generated with medium confidence**

Figure 8: Add preprocessed columns

**A close-up of a document

Description automatically generated with low confidence**

Figure 9: Before and after renaming columns

**Questions & Analyses**

Question 1: What are the academic factors that affect campus placement in students?

Analysis Techniques: Data Manipulation, Visualisation  
Source Code 1.1

Graphical user interface, text, application

Description automatically generated

Figure 10: Code snippet 1.1

Variable *Q1* is assigned to a newly created data frame inclusive of selected columns that will be used for question 1 only. This action is performed by combining the columns as a vector using *c()* function, before the columns are passed into *subset()* and *data.frame()* functions. This process will be replicated throughout all questions.

Students’ degree final exam percentage is binned into 6 distinct categories with an interval of 10: *50-60, 60-70, 70-80, 80-90, 90-100*. A stacked bar chart will be generated using the *ggplot2* package to highlight the different proportions of the 6 categorised degree final exam percentage groups that occupy each placement status (*Placed* or *Not* *Placed*).

Output 1.1

Chart, bar chart

Description automatically generated

Figure 11: Proportion of Degree Final Exam Percentage in Placement Status

As shown in figure 11, we can see that there is little difference between frequencies of students acquiring and not acquiring placement status; even though the later is shown to have a lesser frequency of almost 2000 while the first has surpassed the 2000 mark. The proportions of degree academic percentage categories are approximately the same across different placement status. Degree academic percentage categories of 80-90 and 90-100 take up almost the whole bar (approximately 90%) while the rest are occupied with smaller proportions of 50-60 in both bars, with the addition of 60-70 proportion in “*Not* *Placed*” placement status and 70-80 in “*Placed*” placement status.

Findings 1.1

In India, campus placement is defined as employment opportunities thar are presented to students once they have graduated from university. The objective of introducing this campus placement practice is to ensure university students are able to secure their first job in their career paths regardless of the courses or specialisations they have chosen as their undergraduate or postgraduate studies. Universities in India will often conduct campus placement drives prior to university students’ final examinations in their final year, which undoubtedly motivates students to perform better academically. This justification is supported by the stacked bar of “*Placed*” category, as most students who managed to get campus placement scored final exam results (in their degree year) which falls under the category of either **80% to 90%** and **90% to 100%**.

The same pattern is recognised in the stacked bar of “*Not placed*” category, which could be justified by the drive in students who wish to perform better before their final year so they can score a campus placement more easily. The determination of having to perform better academically can be proven by the increasingly challenging job seeking market in India as there is a serious mismatch in job to candidate ratio across different sectors and industries (Waghmare, 2021). To counteract the possible dilemma of having to be eliminated from a job screening due to intense competition or lack of qualification, these students feel the pressure and need to invest in their own education to land themselves a job immediately upon graduation.

Analysis Techniques: Data Visualisation

Source Code 1.2

Text

Description automatically generated

Figure 12: Code Snippet 1.2

Similar to the source code explanation for the previous graph, postgraduate students’ MBA (Master of Business Administration) final exam percentage is binned into 6 distinct categories with an interval of 10: *50-60, 60-70, 70-80, 80-90, 90-100*. A stacked bar chart will be generated using the *ggplot2* library to highlight the different proportions of the 6 categorised MBA final exam percentage groups that occupy each placement status (*Placed* or *Not* *Placed*).

Output 1.2

Chart, bar chart

Description automatically generated

Figure 13: Proportion of MBA Percentage in Placement Status

Similarly to figure 11, we can see that there is little difference between frequencies of students acquiring and not acquiring placement status; even though both stacked bars have surpassed the 2000 mark. The proportions of MBA (Master of Business Administration) academic percentage categories are approximately the same across different placement status. MBA academic percentage categories of 80-90 and 90-100 take up almost the whole bar (approximately 90%) while the rest are occupied with smaller proportions of 50-60 in both bars, with the addition of 70-80 proportion in “*Not* *Placed*” placement status and 60-70 in “*Placed*” placement status.

Findings 1.2

Similar to the explanation for the previous graph, the second stacked bar chart graph has similar proportion distribution in academic level percentage category (80%-90% and 90%-100%). However, there is a sight difference in comparison to the first stacked bar chart graph. There is lesser proportion of students who score their final exam marks in Master of Business Administration as the form of percentage in between the range of 60%-70% under “*Placed*” category; and even smaller (almost close to none) proportion of students who score between 70%-80% under “*Not placed*” category. Nonetheless, proportions of students who score between 50%-60% seem to not differ much from the first stacked bar chart graph.

Hence, it is safe to assume that we can divide this batch of postgraduate students into two distinct categories:

1. Postgraduate students who are capable of performing well academically
2. Postgraduate students who are well-versed in technical or soft skills

The most common procedure of a campus placement being conducted in India involves this series of steps in order (Team ASM IBMR, 2020):

1. Pre-placement presentation
2. Qualifications
3. Written examination
4. Group discussion
5. Technical knowledge interview
6. Formal interview
7. Post placement discussion

Hence, it is undeniable that a postgraduate student must be able to juggle academics as well as developing their technical skills and polishing their soft skills at the same time to ace through the above listed steps and score themselves a higher chance to be getting placed.

Analysis Techniques: Data Exploration

Source Code 1.3

Text

Description automatically generated with medium confidence

Figure 14: Code snippet 1.3

Various boxplots in correspondence to different academic final exam percentages including but not limited to: *SSCP* (Secondary Education), *HSCP* (Higher Secondary Education), *DEGREEP* (Degree Percentage) and *MBAP* (MBA Percentage) are plotted using the *boxplot()* function. This graph aims to provide clarity on the distribution of students’ academic performance in different stages of academic education levels. These boxplots will be compared against the employability test (column name of *ETESTP*: Employability Test Percentage) boxplot later.

Output 1.3

Chart, box and whisker chart

Description automatically generated

Figure 15: Boxplots of Academic Percentage in Different Stage

According to figure 15, there seems to be no outliers among all students’ academic percentages across different academic stages due to the absence of circles in all box plots. However, we can spot a pattern where academic percentages of Degree, MBA and Employability test seems to have a smaller range in comparison to academic percentages of Secondary School and Higher Secondary School.

Findings 1.3

Across all the boxplots, it seems that secondary school students have a more unsteady academic performance due to both limit ends: close to 40 or even below 40 and close to 100. This phenomenon could be justified by a research that aims to investigate the relationship between high schools’ academic achievement and sense of educational purpose. Results collected from the self-report questionnaire reveal that academic efficacy and educational purpose both play a role in determining a high school student’s sense of rejection and academic achievement (Bilim,v,E., 2016). In order to improve educational purpose in secondary school education, schools and institutes can introduce group or personal counselling programs that help to guide students to develop academic motivation and sense of direction in their education pathway.

Question 2: What are the factors that affect academic performance?

Analysis Techniques: Data manipulation, Data Visualisation  
Source Code 2.1

Graphical user interface, text, application

Description automatically generated

Figure 16: Code snippet 2.1

Average of both parents’ education levels are calculated and assigned to the *AvgPrEdu* variable. The *AvgPrEdu* variable is then later binned into 4 different categories of “*Low*”, “*Medium*”, “*High*” and “*Very* *High*” before getting assigned to a variable named *Avg\_Parents\_Edu\_Level* for better context. Students’ degree final exam percentage is also binned into 3 different categories of “*Low*”, “*Medium*” and “*High*”. A graph is later plotted to investigate the relationship between both variables.

Output 2.1

Chart, scatter chart

Description automatically generated

Figure 17: Average Parents' Education Level Against Degree Percentage

There are two legends to the right which both measure the frequency of a student who falls under the category of either “*Low*”, “*Medium*” or “*High*” while having average parents’ education level of “*Low*”, “*Medium*”, “*High*” and “*Very High*”. The frequency could be measured by checking the colour intensity and size of plotted dots on the graph as indicated by the legends to the right (*1000*, *2000* or *3000*). It is observed that parents of majority of the students who have a “*Medium*” level of degree academic percentage has “*High*” average education level. Interestingly, frequency of students with low degree academic percentage and of parents who have “*Very High*” average education level, is higher than students with low degree academic percentage and of parents who have “*Low*” average education level.

Finding 2.1

The above observation could be explained by a conducted research that parents’ education level of children at 8 years old will determine the educational and occupational successes of their children at 48 years old. Hence, it is predicted that if parents’ educational levels are high; then it is most likely that their children will develop higher educational aspirations and attainment when their children is at 19 years of age (Clearinghouse Technical Assistance Team, 2020). Undoubtedly, a child’s educational aspirations and attainment is correlated with his or her academic performance in school, which explains the reason why frequencies of students achieving “*Medium*” and “*High*” degree academic percentage are higher when average parents’ education levels belong to “*Medium*” and “*High*”.

Analysis Techniques: Data Visualisation  
Source Code 2.2

**Text

Description automatically generated**

Figure 18: Code snipper 2.2

Similar to the previous code blocks, students’ degree academic percentage are binned into 3 different categories namely: “*Low*”, “*Medium*” and “*High*” before a bar chart is plotted against variable *ACTIVITIES*; representative of students’ participation in extra-curricular activities.

Output 2.2

Chart, bar chart

Description automatically generated

Figure 19: Bar Chart of Degree Academic Percentage Groups by Extra Curricular Activities

As shown in the comparison bar chart above, most students have degree academic percentage that falls under the “*Medium*” category. Aside from students who have “*High*” degree academic percentage, more students in other categories seemed to take on extracurricular activities even though the difference compared to students who did not participate in extracurricular activities is not great.

Findings 2.2

There are more students that take on extracurricular activities in the “*Medium*” degree academic percentage group, probably due to the realization of the various benefits that are brought by extracurricular activities. According to research, students who participate in extracurricular activities are proven to perform better during examination and acquired more standardized test scores. Furthermore, they are observed to have higher attendance rate and decreased likelihood in developing problematic behaviours (Ahmad,M et al., 2015). Therefore, schools and universities alike should reinforce the culture of active participation in extracurricular activities by providing adequate facilities for students to conduct club activities out of school hours.

Analysis Techniques: Data Visualisation  
Source Code 2.3

Graphical user interface, text, application

Description automatically generated

Figure 20: Code snippet 2.3

Similar to the previous code blocks, students’ degree academic percentage are binned into 3 different categories namely: “*Low*”, “*Medium*” and “*High*” before a bar chart is plotted against variable *INTERNET*; representative of students’ accessibility towards internet at their own homes.

Output 2.3

Chart, bar chart

Description automatically generated

Figure 21: Bar Chart of Degree Academic Percentage Groups by Internet Access At Home

Similar to the previous comparison bar chart, most students have degree academic percentage that falls under the “*Medium*” category. It is observed that regardless of different degree academic percentage categories, there are more students who have internet access at home.

Findings 2.3

It seems that students who have access to the internet at home tend to perform better academically as indicated by the higher proportions of blue bars under “*Medium*” and “*High*” categories of degree academic percentage. This is very true as revealed in an experiment where students with poor internet connection find themselves suffering from educational setbacks and are more likely to not have plans for attending colleges or universities. In contrary to that, students with high broadband access are observed to develop better digital skills, more intended to continue their studies in STEM subjects which led them to strive and flourish in high-paid STEM careers in the near future (Bauer,J et al., 2020).

Question 3: What are the academic factors that affect campus placement in students?

Analysis Techniques: Data Manipulation, Data Visualisation  
Source Code 3.1

Graphical user interface, text, application

Description automatically generated

Figure 22: Code snipper 3.1

Similar to the previous code blocks, students’ degree academic percentage are binned into 3 different categories namely: “*Low*”, “*Medium*” and “*High*” before a bar chart is plotted against variable *MJOB*; representative of students’ mothers’ occupation in the groups of: “*at\_home*”, “*health*”, “*other*”, “*services*” and “*teacher*”.

Output 3.1

Chart, bar chart

Description automatically generated

Figure 23: Bar Chart of Degree Academic Percentage Groups by Mother's Occupation

In this comparison bar chart, we could see that mothers of students who have “*High*” degree academic percentage have unspecified “*Other*” occupations. In the meantime, mothers of students who have “*Low*” degree academic percentage have occupations in the “*Health*” industry.

Findings 3.1

According to studies, it is stated that parental occupational attributes contribute has significant influence on students’ academic performance. That being said, children of parents that have regular jobs and income are more likely to perform better academically. Possible factors that contribute to this scenario could be this group of students do not have to worry about their basic needs such as mealtimes, shelter, education etc. not being met when their parents are able to provide for their necessities. Furthermore, their parents are most likely to work in stable environments hence they might offer educational help to their children after they came home as they are not affected by long travel journey (Atolagbe,A et al., 2019). Therefore, the government should seek to reinform regular salary payment for parents who work as government employees and encourage parents to be more involved their children’s academic matters.

Question 4: What are the factors that affect salary?

Analysis Techniques: Data Manipulation, Data Visualisation  
Source Code 4.1

Graphical user interface, text, application, email

Description automatically generated

Figure 24: Code snippet 4.1

The “*scales*” package is acquired and loaded with the help of *require()* function. This package is required to help with scaling so that it provides more accurate and better data visibility on the scaling of *SALARY* variable (R Documentation, n.d.). The “*plyr*” package is also loaded in order to use the *ddply()* function to apply *mean()* function in *SALARY* column of each gender (*F* or *M*) before combining the results back to subset of *Q4* dataframe. Two histograms are plotted with the help of *facet\_grid()* function which presents the two histograms in panels separated by two distinctive categories of *GENDER*.

Output 4.1

Chart, bar chart

Description automatically generated

Figure 25: Distribution of Salary in Genders

From the two displayed histograms, we could see that both histograms are right-skewed. This is because salary among students in both genders peaked at approximately 300,000 while the lowest salary a student can acquire is 200,000; and the highest is at 500,000. The mean of salary is highlighted by a red-coloured dashed line in both histograms of both genders.

Findings 4.1

From the above figure, what we can infer is that salary for fresh graduates or postgraduate students typically fall within the 300, 000 mark regardless of different genders. Even though there are occasional spikes where students score the lower end of the salary deal in the range between 200,000 to 300,000; some manage to score better deals at around 400,000. Very few students managed to get anything higher beyond that mark, expect a few outliers who hit the 500,000 mark at the end of the range. Even though India is notorious for its gender wage gap, the above figure did not paint the picture. Hence, we can assume that the provided dataset could be improved in future studies as this dataset could be inaccurate or there are potential hidden data quality issues.

Analysis Techniques: Data Visualisation  
Source Code 4.2

Graphical user interface, text, application, email

Description automatically generated

Figure 26: Code snippet 4.2

Similar to the previous source code explanation, one of the differences in this source code explanation is that the *mean()* function is applied to *SALARY* column of each category in *PAID* column, which is representative of whether the specific student has paid for extra classes (Mathematics or Portuguese) within the course subject. The second difference is that the resulting plotted histograms will be grouped by the *facet\_wrap()* function which has a different layout (side to side) than *facet\_grid()* function (up and down) in accordance to *PAID* column.

Output 4.2

Chart, bar chart

Description automatically generated

Figure 27: Distribution of Salary Against Paid

From the two displayed histograms, we could see that both histograms are right-skewed. This is because salary among students in both *PAID* variable categories (“*yes*” and “*no*”) peaked at approximately 300,000 while the lowest salary a student can acquire is 200,000; and the highest is at 500,000. The mean of salary is highlighted by a red-coloured dashed line in both histograms of both *PAID* variable categories. However, one significant difference between the previous graph and this graph is that frequency of students who did not pay for extra classes and get the expected mode salary is higher than those who had paid for extra classes.

Findings 4.2

Similar to the previous figure, there is little difference in variation of both histograms when we perform a side-to-side comparison. However, we could safely say that the *PAID* variable plays a role in determining a student’s salary even though the effect is not too significant. This is because it is observed that frequency of students paying for extra classes and has a salary pay of approximately 300,000 is lower than students who did not pay for extra classes. This could be justified by the fact that students who did not pay for extra classes are already well-versed in both Mathematics and Portuguese, hence there is no need for them to pay for extra classes; and employers are more likely to hire them as they do not require additional employee training given that the job scope requires these students to out their knowledge in Mathematics and Portuguese to use.

Question 5: What are the factors that affect employability test?

Analysis Techniques: Data Manipulation, Data Visualisation  
Source Code 5.1

Text

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Figure 28: Code snippet 5.1

The *geom\_bin2d()* function is used to plot a heatmap using two variables namely *HSCP* and *ETESTP* to investigate the correlation between higher secondary education academic percentage and employability test. The limits of both x and y axes are also pre-set in accordance to the lowest and highest values of both variables.

Output 5.1

Graphical user interface, chart

Description automatically generated

Figure 29: Heatmap of Higher Secondary Education Percentage Against Employability Test

From the heatmap, we can infer that most students have their *HSCP* (Higher Secondary Education Academic Percentage) and *ETESTP* (Employability Percentage) fall within the approximate range of 50 to 95. The colour intensity of squares tell us the frequency of students who managed to achieve the specific *HSCP* and *ETESTP*. However, there are a few outliers that stand out where students achieved both *HSCP* and *ETESTP* of lesser than 50 or higher than 95.

Findings 5.1

A research has concluded in general, employers tend to regard a potential employee’s academic qualifications and achievements to fall under reasonable expectations; even though candidates who managed to fulfil this criteria do not necessary find themselves hired just because of this sole factor. This is because employers nowadays also seek out for achievements outside of the academic sector, namely soft skills as a person’s employability should not be limited to and be determined by academic prowess alone. The most important element of keeping a person’s employability in top-notch condition is life-long learning where individuals have to take the time to polish their skillsets and perform continuous learning in order to stay relevant in their existing working industry (Brassey, et al., 2019).

Analysis Techniques: Data Visualisation  
Source Code 5.2

Text

Description automatically generated

Figure 30: Code snippet 5.2

The *geom\_density()* function is used to plot a density plot using two variables namely *ETESTP* and *WORKEX.* This density graph aims to display the distribution of students’ employability test under different categories of *WORKEX* variable (*Yes* or *No*), representative of students’ working experience.

Output 5.2

Chart, histogram

Description automatically generated

Figure 31: Density Plot of Employability Test in Work Experience

In the above density plot, there are two highlighted density areas where yellow represents students who do not have any working experience while grey is representative of students who have working experience. Both density areas are plotted to view the distribution of *ETESP* in each category of *WORKEX* (working experience) variable. It is observed that density area plotted under students who have working experience is less consistent that those who do not have; and has a higher density value which peaks at approximately 0.023 and at *ETESP* of 60. The similarity between both density areas is that they both curve downwards towards the end starting from *ETESP* of 90.

Findings 5.2

Both density curves under two categories of *WORKEX* variable are right-skewed. This shows that the mean of employability test is greater than the median (Zach, 2020). Furthermore, we could see that there are more students who manage to score an employability test of 60% when they have working experience. These students have the upper hand comparing to those who do not have any working experience as a majority of them score an employability test of less than 55%; hence highlighting the fact that students should focusing on scoring placement as it would be a valuable addition to a student’s employability in the future as they eventually leave their first job for the better.

**Extra features**

1. Cut() function

**Text

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Figure 32: cut() function

Chart, bar chart

Description automatically generated

Figure 33: Binned degree percentages

The *cut()* function provides more visibility on the distribution of students who score different grades of final exam academic percentages by binning *DEGREEP* variable into 5 different categories as shown in the legends on the right side of figure 33.

1. Scales package

**Text

Description automatically generated**

Figure 34: scales package

Chart, bar chart

Description automatically generated

Figure 35: Customised x axis values

The *scales* package allows us to have our own customised x axis values as shown in figure 35, where appropriate salary values are shown in the x axis instead of cumulative addition of salary values.

1. Geomvline() function

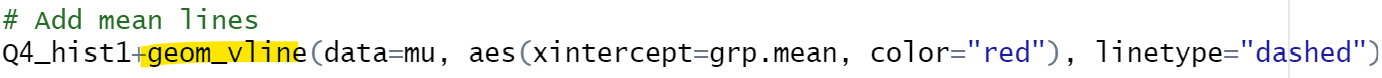


Figure 36: geomvline() function

Chart, bar chart

Description automatically generated

Figure 37: Mean lines added

The *geom\_vline()* function is used to draw a horizontal line to indicate mean values in *SALARY* variable as shown in figure 37 (in the form of red dashed line).

1. Geom\_bin2d() function

A picture containing chart

Description automatically generated

Figure 38: geom\_bin2d() function

Graphical user interface

Description automatically generated

Figure 39: Heatmap

The *geom\_bin2d()* function allows us to plot a heatmap using 2 variables (in the case it is *HSCP* and *ETESTP* variables) to view the correlation between them.

**Conclusion**

In conclusion, all of the questions stated in introduction are answered with the graphs generated from data exploration, data manipulation and data visualisation; with accompaniment of with in-dept analyses and findings. Assumptions included in analyses and findings are made based on personal speculations with additional help from available online resources. Now that a thorough analysis has been conducted on this campus recruitment dataset, the marketing team of the university should be able to make informed decisions on how to increase placement rate among students.

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