Data Science In Practice - Feature engineering

EPF - P2023
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ÉCOLE D'INGÉNIEUR·E·S

IV. Data Science in practice: Feature engineering

1. Introduction
2. Handling numerical features
3. Handling categorical features
4. Using interaction features
5. Feature selection

Introduction

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- It’s a very important step in the **ML pipeline**, it enables the model to output predictions of a **better quality**

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$$Price = \beta_0 + \beta_1 . L + \beta_2 . W + \beta_3 . A$$

$$with \quad A = L . W$$

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- We will try to cover some of the most common feature engineering techniques

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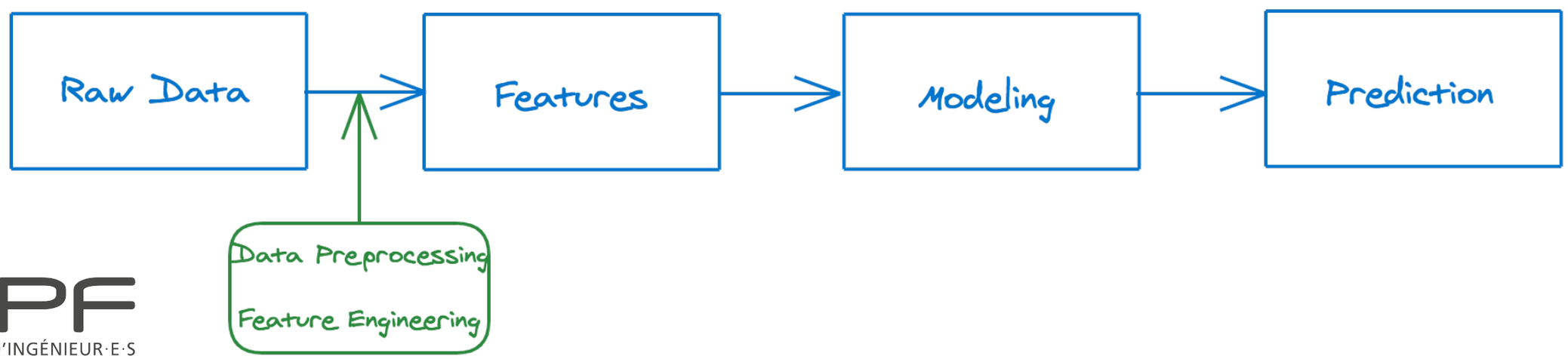

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- Does a large listen count mean the user really likes the song and low listen count mean the user does not like the song?

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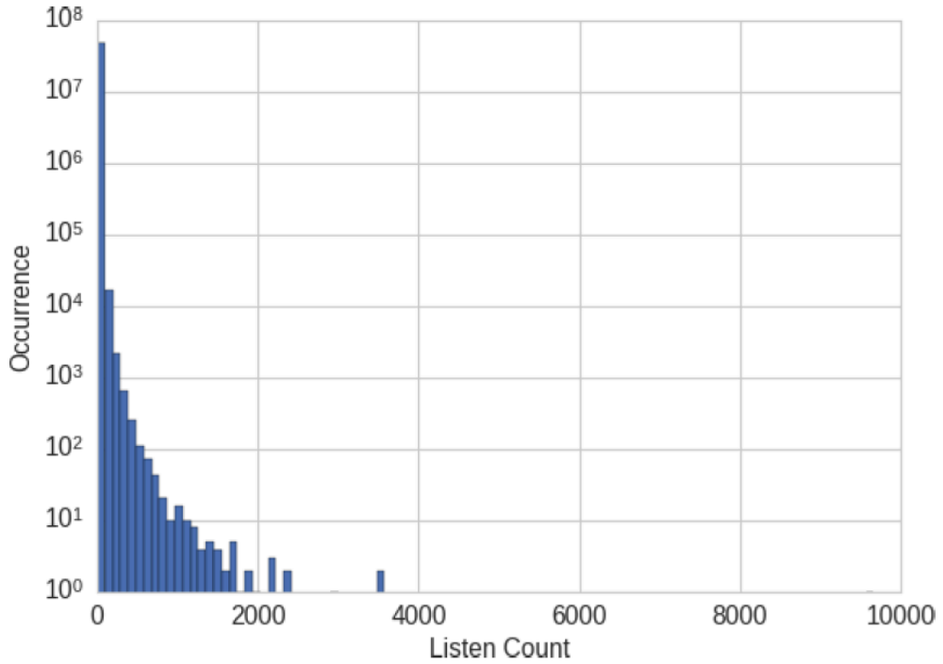

Histogram of listen counts in the dataset

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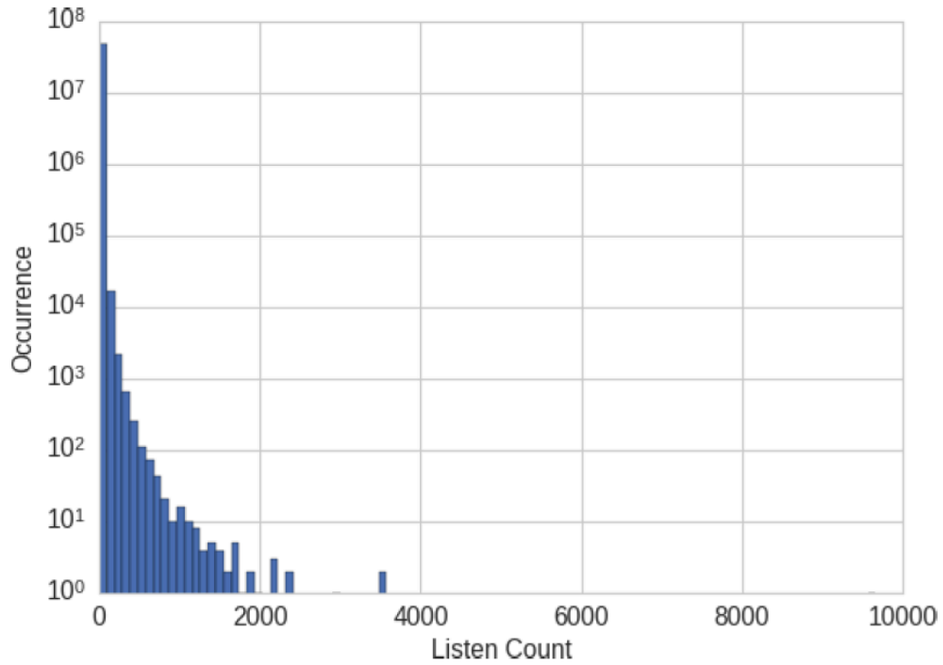

Histogram of listen counts in the dataset

- The data shows that 99% of the counts are below 24, there are some counts in the thousands, these data points are called **outliers**

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- We can see that the listen counts is not a robust measure of user taste. Some users might put their favorite musics in infinite loop, others might like to listen to them on a less frequent basis

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- We can see that the listen counts is not a robust measure of user taste. Some users might put their favorite musics in infinite loop, others might like to listen to them on a less frequent basis

- A more robust measure of user taste is to **binarize (0/1)** these counts: If the user listened to a song more than once, we can count it as the user liked this song

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- Let’s take a look at the data

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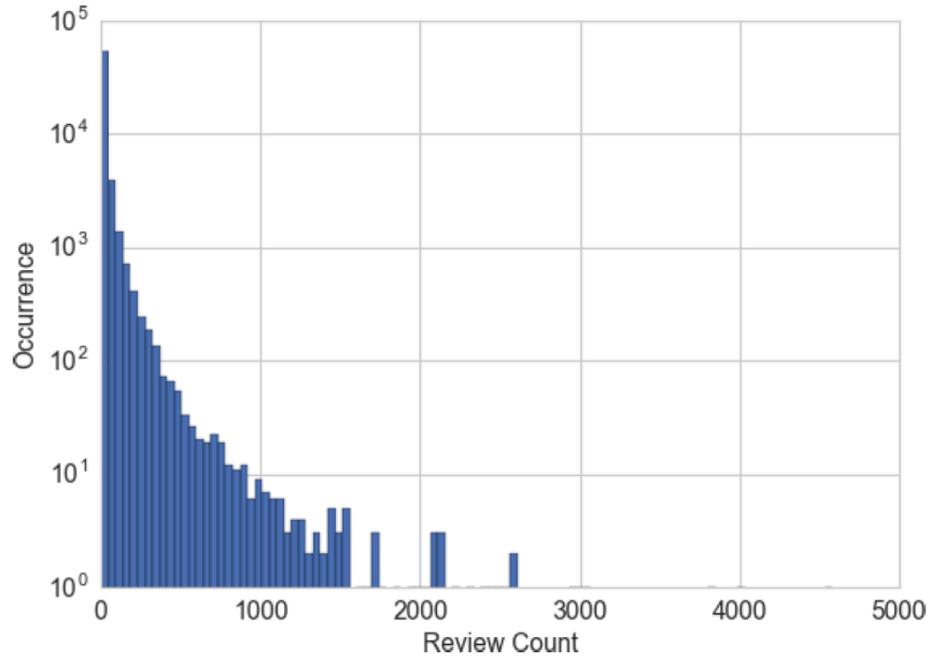

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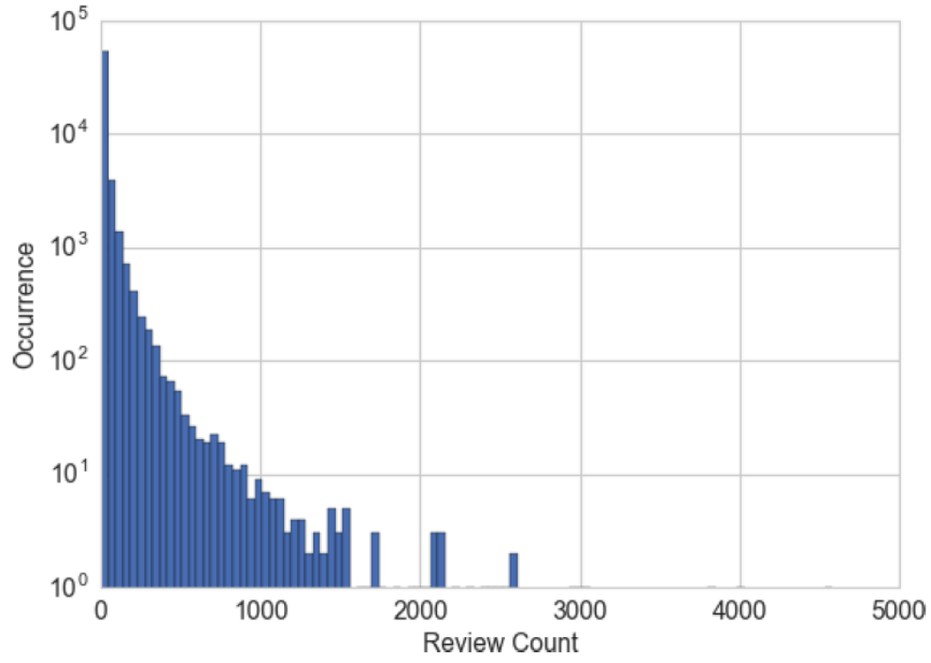

Histogram of review counts in the dataset

- The raw counts span over several order of **magnitudes**, this can be problematic for linear models as only **one coefficient** is associated to the feature. This coefficient should work for all the orders of magnitude

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3. Quantile binning: dividing the data into equal portions by using the quantiles of the distribution

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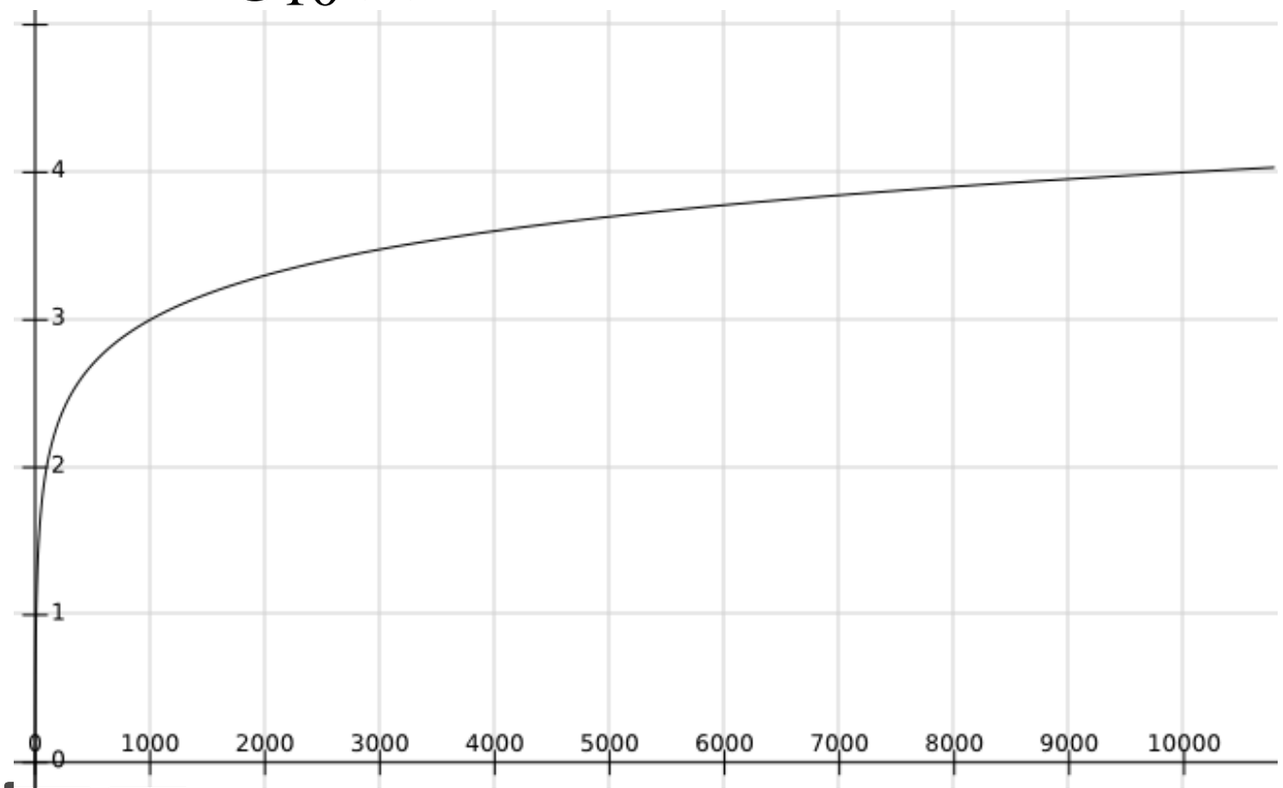

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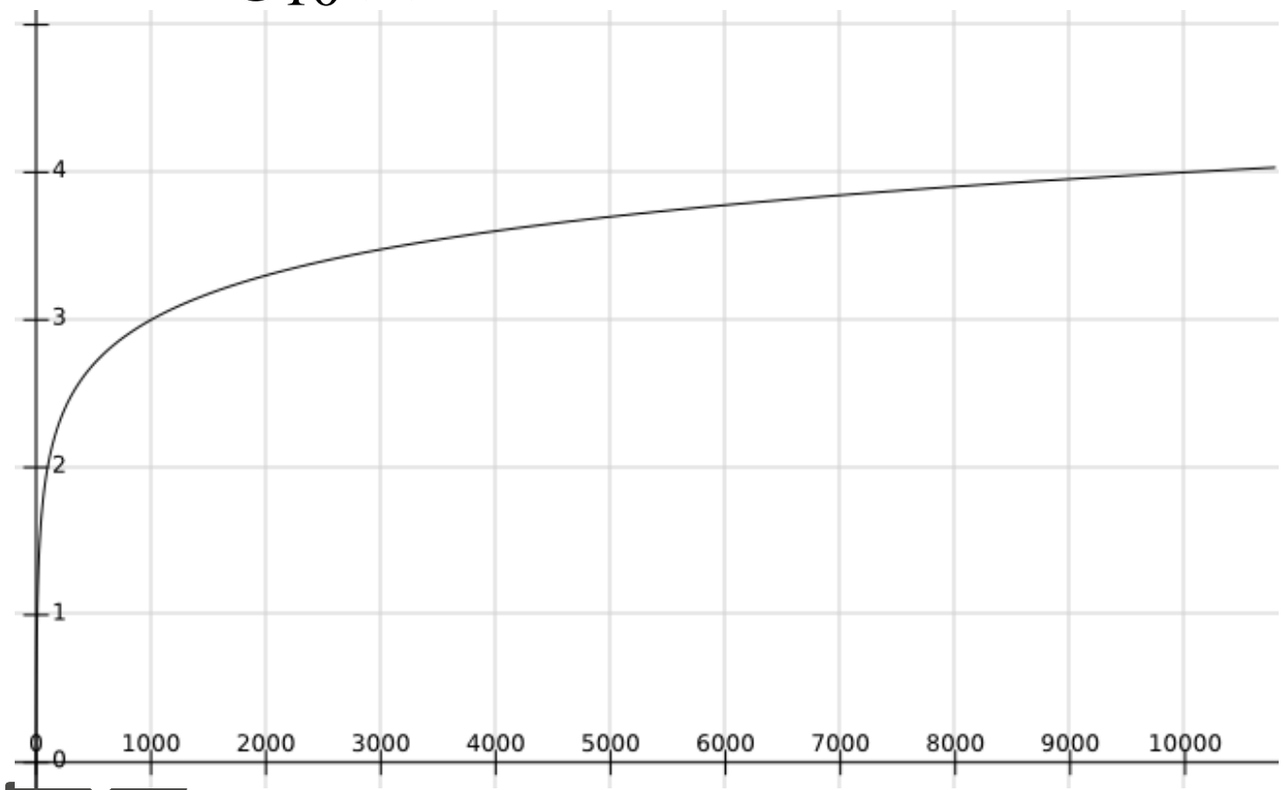

We can see that this function maps:

- The range of]0,1] to]-inf,0]
- The range of [1,10] to [0,1]
- The range of [10,100] to [1,2]
- …

➡ The log functions compresses the range of large numbers and expands the range of small numbers

➡ It's a powerful tool to deal with positive numbers with a heavy-tailed distribution

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- The raw distribution is **skewed** to the left, we need to apply a log transformation

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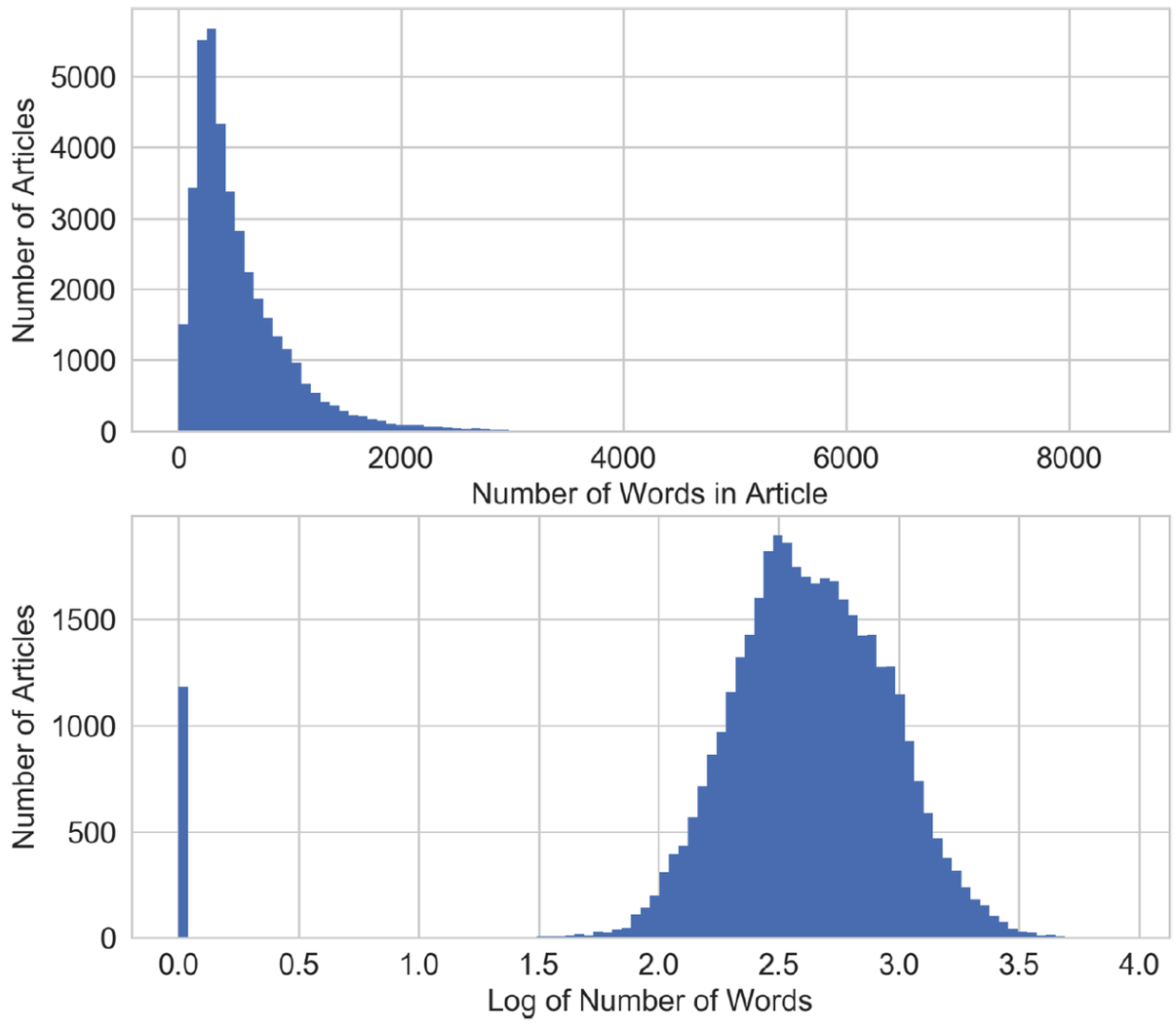

Comparison of word counts in news articles before (top) and after (bottom) log transformation

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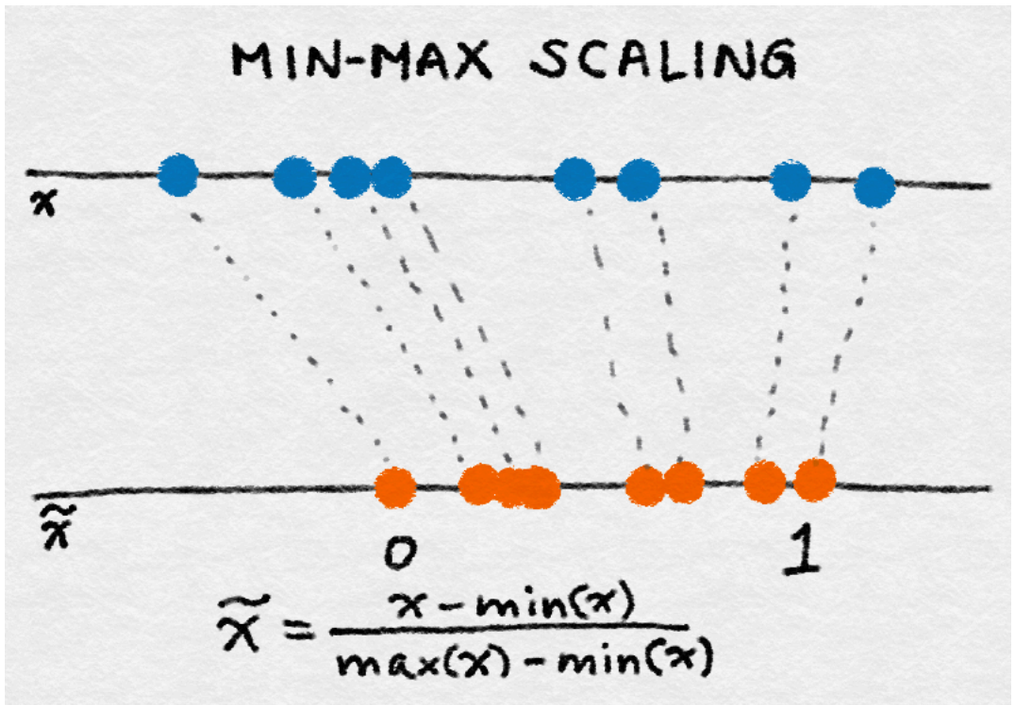

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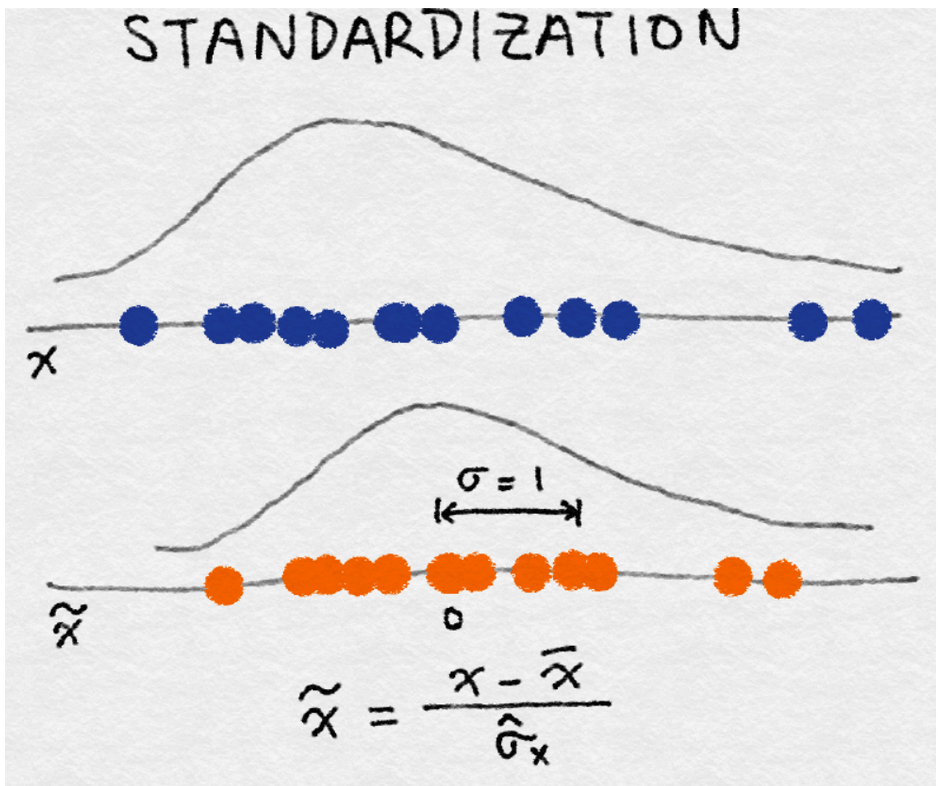

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- Numerical feature scaling is very useful in datasets containing features that **differ wildly in scale**, especially if we're using **linear models**. Random Forests on the other hand are quite robust to features' scale differences

- It can also be shown that numerical feature scaling can bring **more stability** and **quicker convergence** for gradient descent

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- Ex: A stock price is numerical, a company id is categorical

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- Ex: One-hot-encoding a categorical variable with 3 categories

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Paris	0	1	0
Marseille	0	0	1

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- These 2 methods are not enough to deal with **large categorical variables**, we need some alternatives

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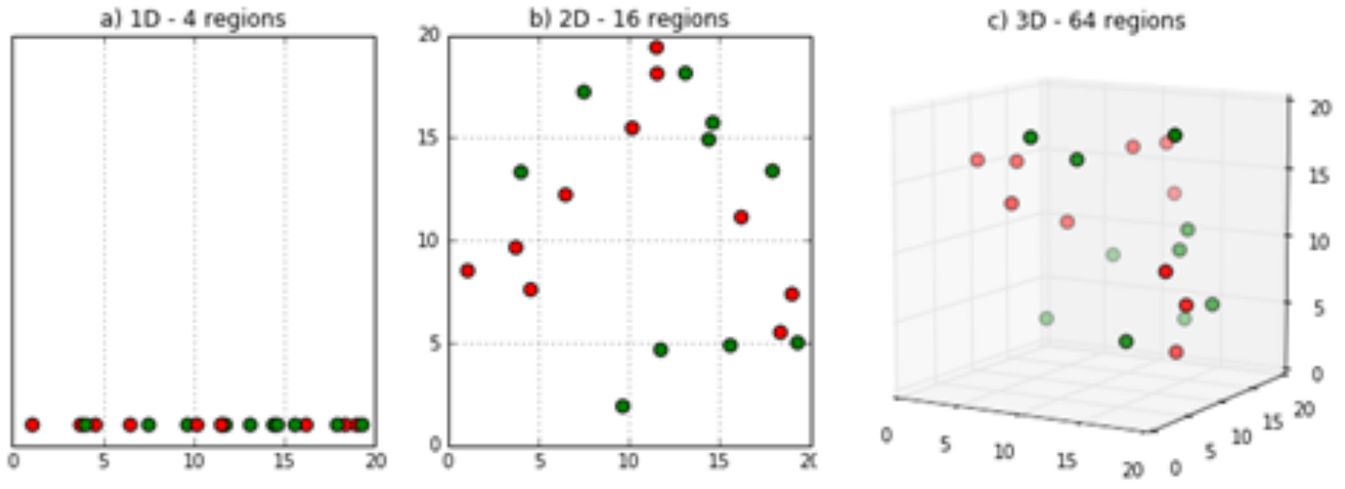
- This can lead to a common issue known as the **curse of dimensionality**: As the volume of the features space grows, the available data becomes **more sparse**

Handling categorical features

- Illustration of the curse of dimensionality



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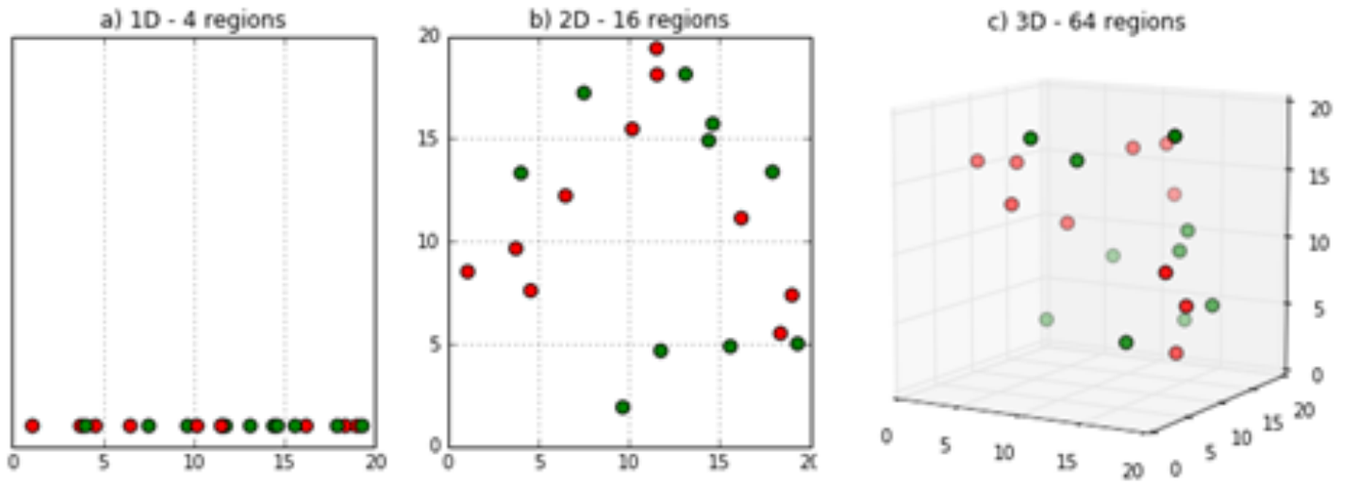

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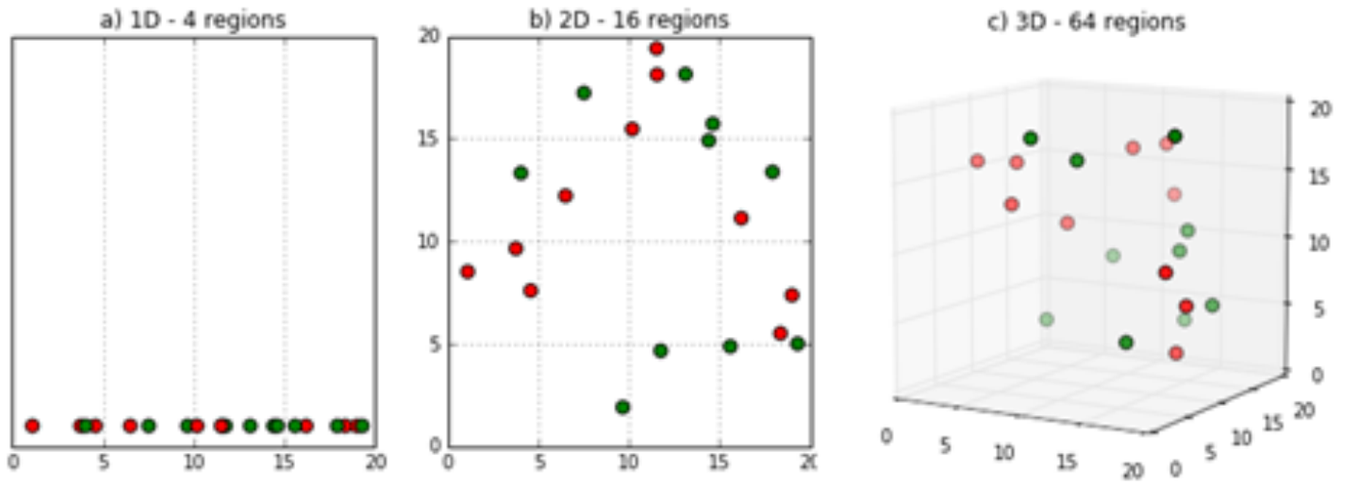

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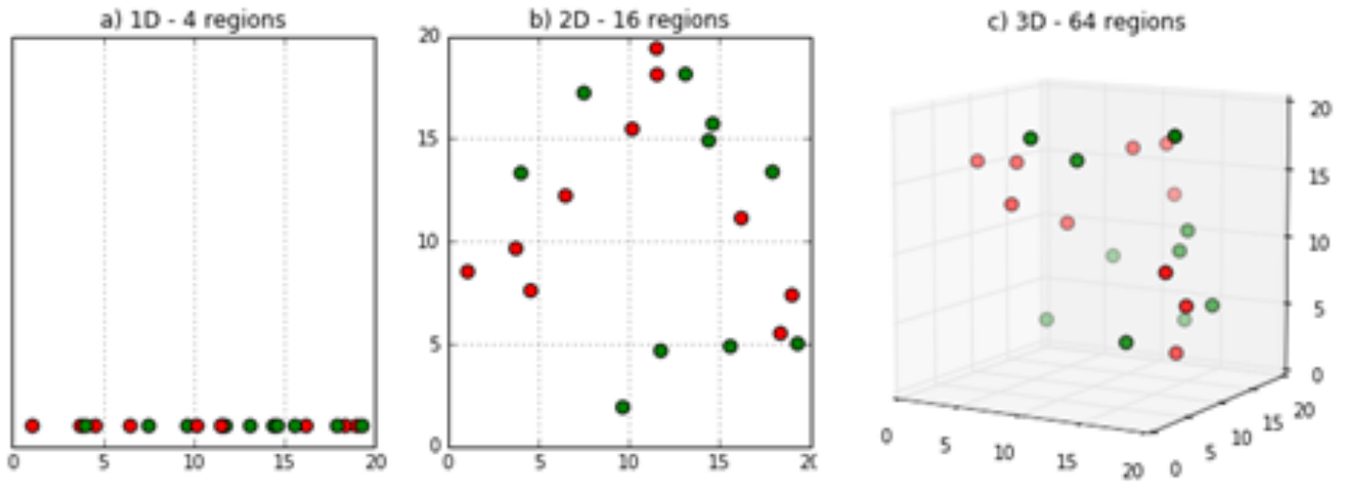
- As a consequence we will need **more data** to obtain **statistical significance**

Handling categorical features

- Illustration of the curse of dimensionality



- As the **dimension** of the space **grows**, the given data fills **less and less space**
- As a consequence we will need **more data** to obtain **statistical significance**
- Fortunately, there are some techniques to deal with very large categories: hashing, bin counting, …

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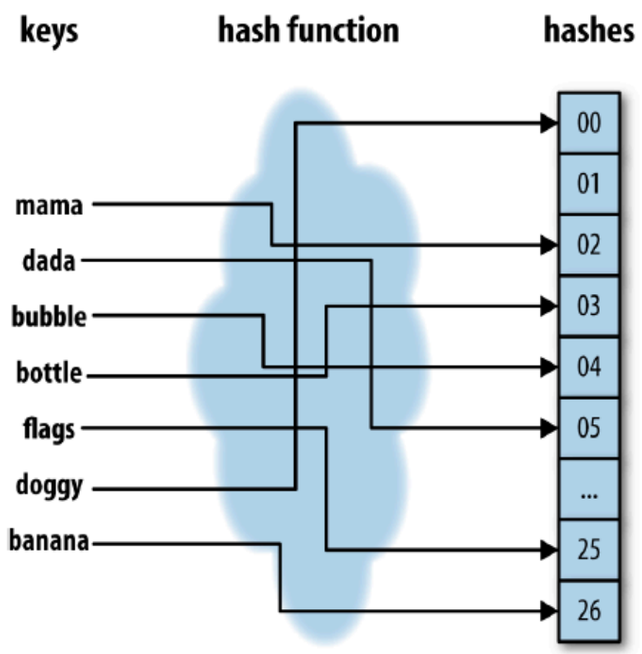
$$f(X) = \textbf{HASH}(X)\,\%\,M$$



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- We can show that a controlled collision rate does not deteriorate the model's performances

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  - Not scalable: cannot support high-cardinality attributes

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  - Not adaptive: doesn’t support drift in attribute values

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  + Scalable: no mapping tables

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  ➡ These features can have extremely large cardinalities (thousands, millions…)

Handling categorical features

- Example: Click prediction with Bin Counting

userId	adId	…	click
9cee4db5	026244a3303d	…	1
43e6b34c	026244a3303d	…	1
bf7c2071	7cf137c0d1d2	…	0
d47ee3d0	de13539e3365	…	0
d47ee3d0	de13539e3365	…	0
43e6b34c	7cf137c0d1d2	…	1
9cee4db5	8a14d3c7ebfe	…	1
9cee4db5	026244a3303d	…	1
…	…	…	
bf7c2071	8a14d3c7ebfe	…	0

Handling categorical features

- Example: Click prediction with Bin Counting

userId	NB click	NB no-click	Conditional click Probability
9cee4db5	11	5	0.6875
43e6b34c	12	6	0.6667
bf7c2071	2	4	0.3334
d47ee3d0	1	3	0.25
…	…	…	…

Handling categorical features

- Example: Click prediction with Bin Counting

userId	NB click	NB no-click	Conditional click Probability
9cee4db5	11	16	0.6875
43e6b34c	12	18	0.6667
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…	…	…	…

adId	NB click	NB no-click	Conditional click Probability
026244a3303	59	92	0.6413
7cf137c0d1d2	66	94	0.7021
de13539e336	20	42	0.4761
8a14d3c7ebfe	54	78	0.6923
…	…	…	…

Handling categorical features

- Example: Click prediction with Bin Counting

userIdProcessed	adIdProcessed	…	click
0.6875	0.6413	…	1
0.6667	0.6413	…	1
0.3334	0.7021	…	0
0.25	0.4761	…	0
0.25	0.4761	…	0
0.6667	0.7021	…	1
0.6875	0.6923	…	1
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$$\textbf{oddsRatio}(user = 9cee4db5) = \frac{P(click \mid user = 9cee4db5) \quad / \quad P(noclick \mid user = 9cee4db5)}{P(click \mid user \neq 9cee4db5) \quad / \quad P(noclick \mid user \neq 9cee4db5)} = 0.7902$$

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  - Odds ratio can be interpreted as « How much more likely is user 9cee4db5 to click than to not click, compared to others »

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  ± Risky: should be handled with great caution, can introduce data leakage

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➡ **Information leakage** happens when some information that the model is **not supposed to have access to becomes available to it**, thus giving the model an **unfair advantage**. For example, if the input variables for a row i contains information about the target variable of row i

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➡ This can also happen if test data is leaked into training data, or if future data is leaked into past data

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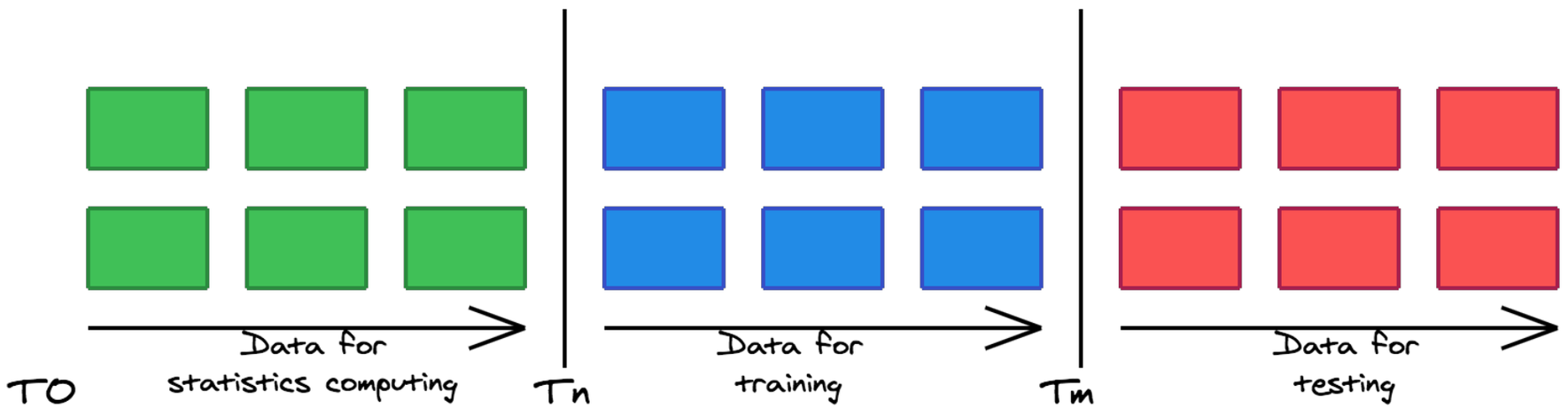

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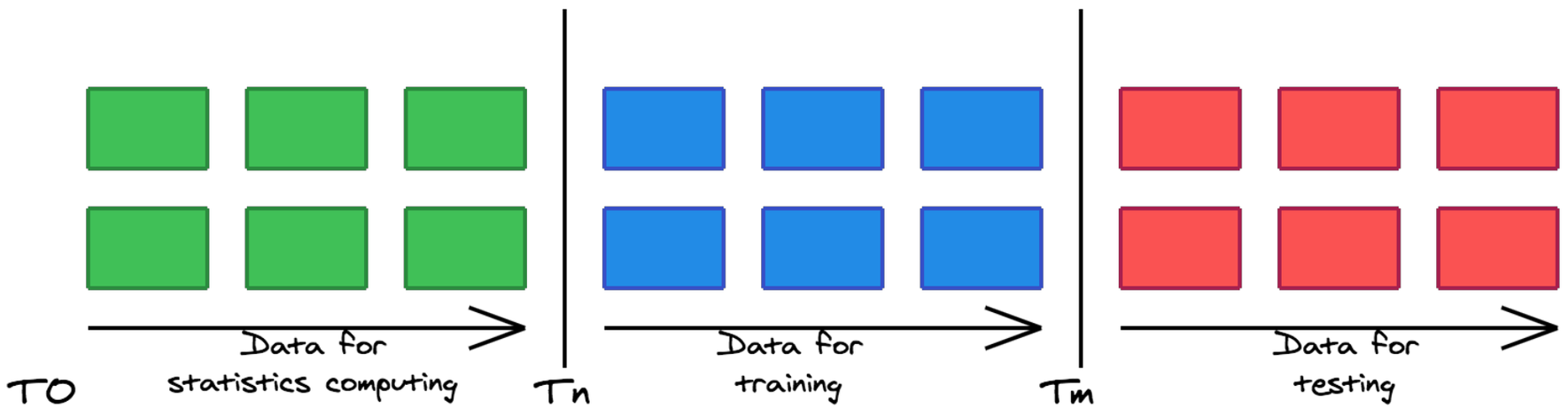

  - Use **leave-one-out** counting associated with a **small random noise** to cover for for any potential data-leakage

Handling categorical features

- Summary

Plain one-hot encoding	
Pros	- Easy to implement - Accurate - Feasible for online learning
Cons	- Computationally inefficient - Does not adapt to growing categories - Only feasible for linear models

Handling categorical features

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Feature hashing	
Pros	- Easy to implement - Makes model training cheaper - Easily adaptable to new categories - Easily handles rare categories
Cons	- Only suitable for linear models - Hashed features are not interpretable - Not always yielding a good accuracy

Handling categorical features

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Bin counting	
Pros	- No computational burden at training time - Suitable for all sorts of models - Easily adaptable to new categories - Easily handles rare categories with back-off - Interpretable
Cons	- Requires historical data - Not suitable for online learning - High potential of information leakage

Using interaction features

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- Eg:

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$$y = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \beta_{1,2}(x_1 \,\&\, x_2) + \beta_{1,3}(x_1 \,\&\, x_3) + \ldots$$

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- **Tree-based models** can approximate these interactions by doing splits based on different features. However, it can be worth it to help the models by feeding them interactions that seem interesting

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  ➡ **Exploratory data analysis**

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- The results of the EDA can influence **subsequent decisions** on how we deal with the task at hand

Exploratory Data Analysis

- The goal of doing statistical analyses of the data is to determine the **quality of the features** and their **predictive power** in contrast with the target value

- The data exploration is conducted from three different angles:
  - **Descriptive**
  - **Correlative**
  - **Contextual**

Exploratory Data Analysis

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Attribute type	Statistic/calculation	Details
Common	Data type	Attribute's data type
	Missing values	Percentage of missing values
Numerical	Quantile statistics	Q1, Q2, Q3, Q3, min, max, range
	Descriptive statistics	Mean, mode, standard deviation, median absolute deviation, kurtosis, skewness
	Distribution histogram	Based on the appropriate number of bins
Categorical	Cardinality	Number of unique values for the categorical feature
	Unique counts	Number of occurrences for each unique value of the categorical feature

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  - **Qualitative analysis:** computation of the descriptive statistics of the target numerical or categorical attributes against each unique value of the independent feature

  - **Quantitative analysis:** testing the relationship between X and Y based on a hypothesis-testing framework

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  - **Time-based analysis**: in many real-world datasets, the timestamp is one of the **key contextual** information. It's very important to understand the characteristics of the data along with the time dimension with different granularities. Ex: number of records per time interval, number of unique values per time interval, descriptive statistics per time interval, …

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  - **Agent-based analysis**: another common attribute is unique identification (websiteId, userId, …). With these ID attributes, we can perform descriptive statistics per agent. Ex: average number of transaction on a specific website in X months, average number of unique customers per specific store in X months, …

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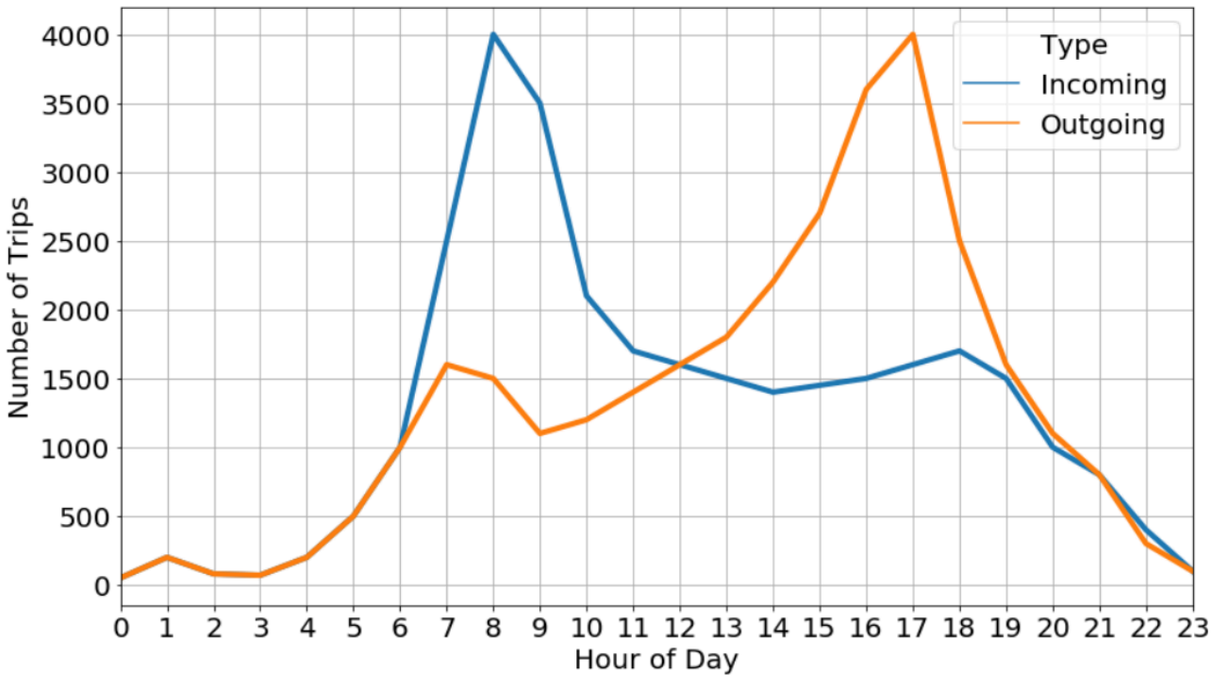
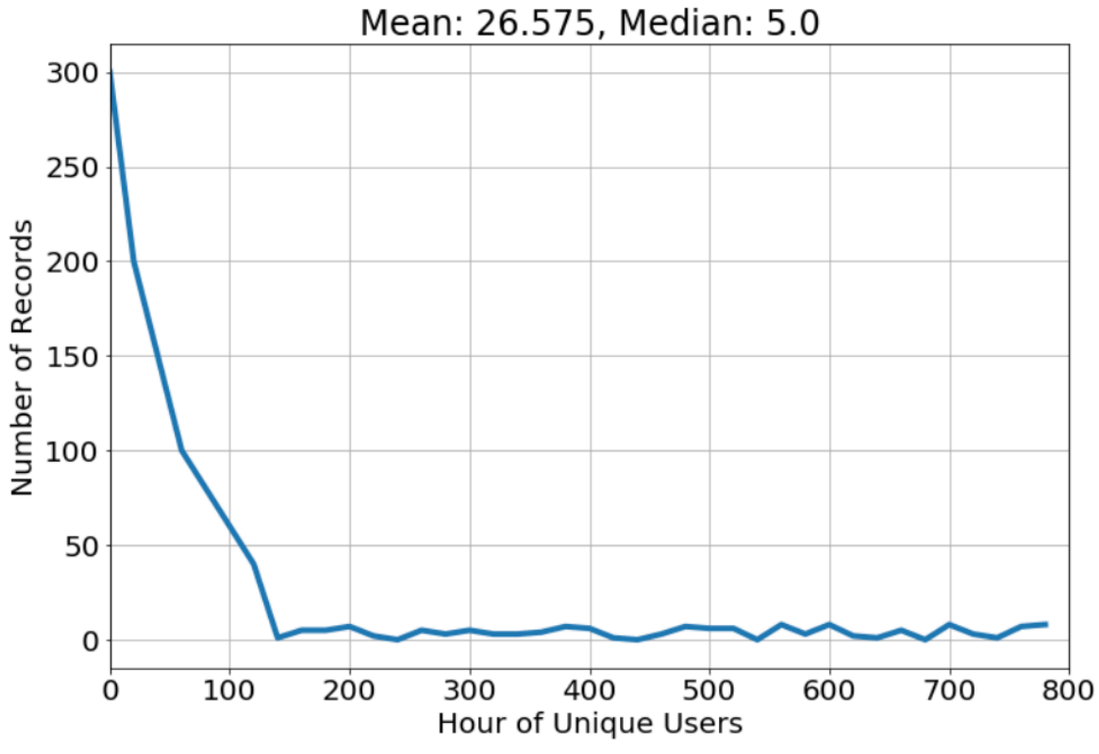


Average number of train trips per hour originating from and ending at one particular location



Histogram of the number of transactions (combined call, SMS, and internet) made per user in a week

Exploratory Data Analysis

- Let’s illustrate this with a concrete example: The census income dataset

workclass	education	marital_ status	occupation	relationship	race	sex	native_ country	income_ bracket
Private	9th	Married-civ-spouse	Other-service	Wife	Black	Female	United States	<=50K
Private	9th	Married-civ-spouse	Exec-managerial	Wife	Asian Pac Islander	Female	United States	>50K
Private	9th	Married-civ-spouse	Machine-op-inspct	Wife	White	Female	United States	>50K
Private	9th	Married-civ-spouse	Exec-managerial	Wife	White	Female	United States	<=50K
Private	9th	Married-civ-spouse	Tech-support	Wife	White	Female	United States	<=50K

age	functional_weight	education_num	capital_gain	capital_loss	hours_per_week
39	297847	5	3411	0	34
72	74141	5	0	0	48
45	178215	5	0	0	40
31	86958	5	0	0	40
55	176012	5	0	0	23

Exploratory Data Analysis

- **Descriptive** data analysis:

Feature	Type	% Missing
age	Integer	0
workclass	String	0
functional_weight	Integer	0
education	String	0
education_num	Integer	0
marital_status	String	0
occupation	String	0
relationship	String	0
race	String	0
sex	String	0
capital_gain	Integer	0
capital_loss	Integer	0
hours_per_week	Integer	0
native_country	String	0
income_bracket	String	0

Exploratory Data Analysis

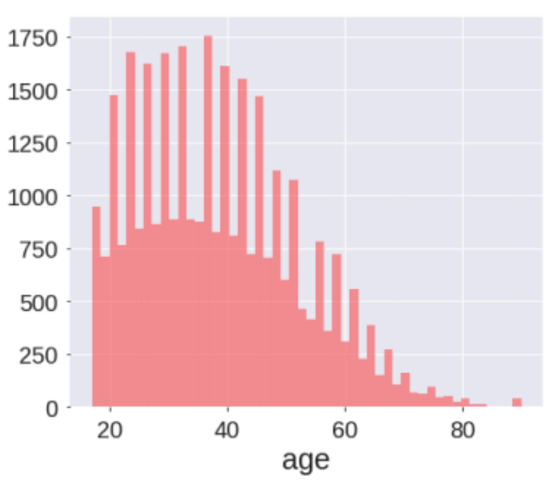
- **Descriptive** data analysis: numerical features

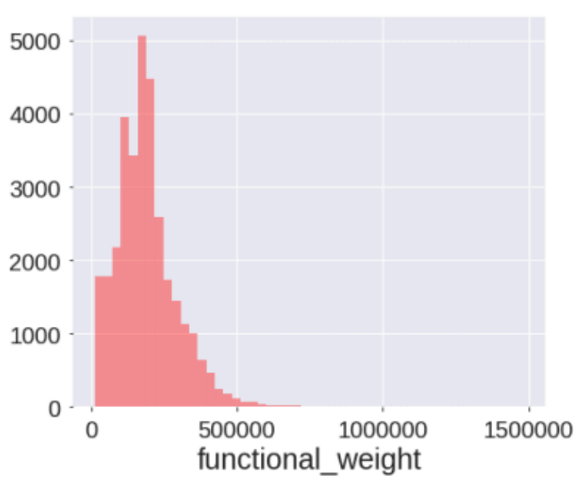
	max	range	IQR	mode	mad	kurtosis	skewness
age	90	73	20	36	11.189182	-0.166127	0.558743
functional_weight	1484705	1472420	119224	123011	77608.21854	6.218811	1.44698
education_num	16	15	3	9	1.903048	0.623444	-0.311676
capital_gain	99999	99999	0	0	1977.373437	154.799438	11.953848
capital_loss	4356	4356	0	0	166.462055	20.376802	4.594629
hours_per_week	99	98	5	40	7.583228	2.916687	0.227643

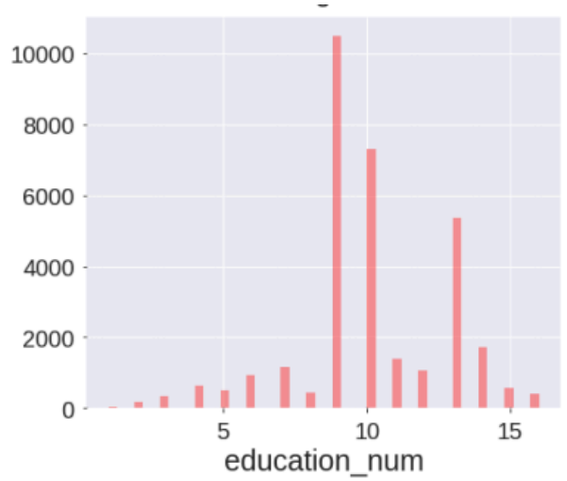
	mean	std	min	25%	50%	75%
age	38.581647	13.640433	17	28	37	48
functional_weight	189778.3665	105549.9777	12285	117827	178356	237051
education_num	10.080679	2.57272	1	9	10	12
capital_gain	1077.648844	7385.292085	0	0	0	0
capital_loss	87.30383	402.960219	0	0	0	0
hours_per_week	40.437456	12.347429	1	40	40	45

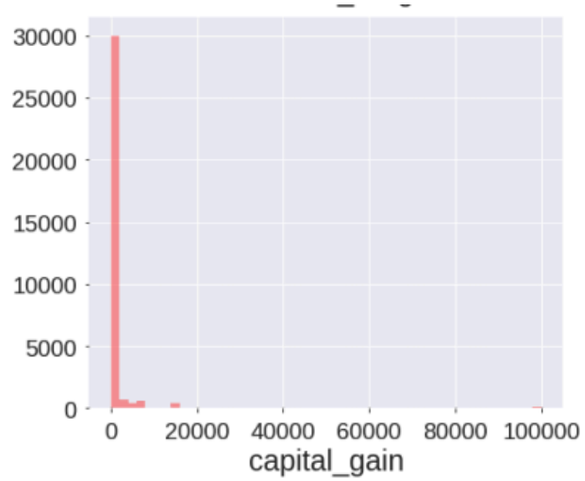
Exploratory Data Analysis

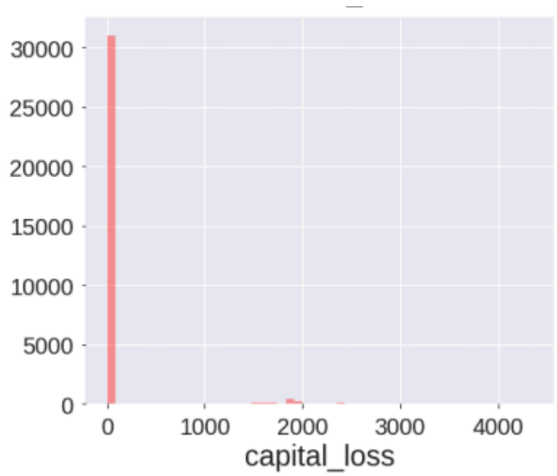
- **Descriptive** data analysis: numerical features

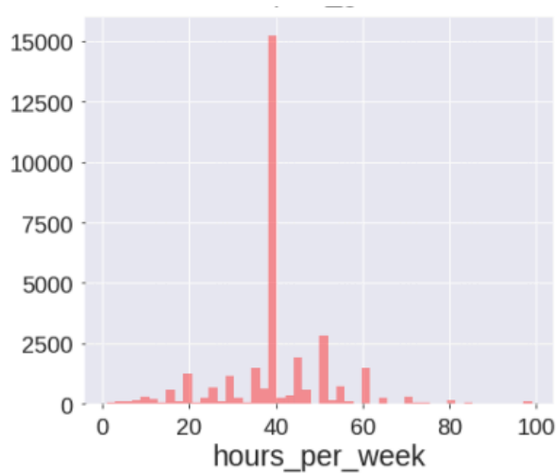






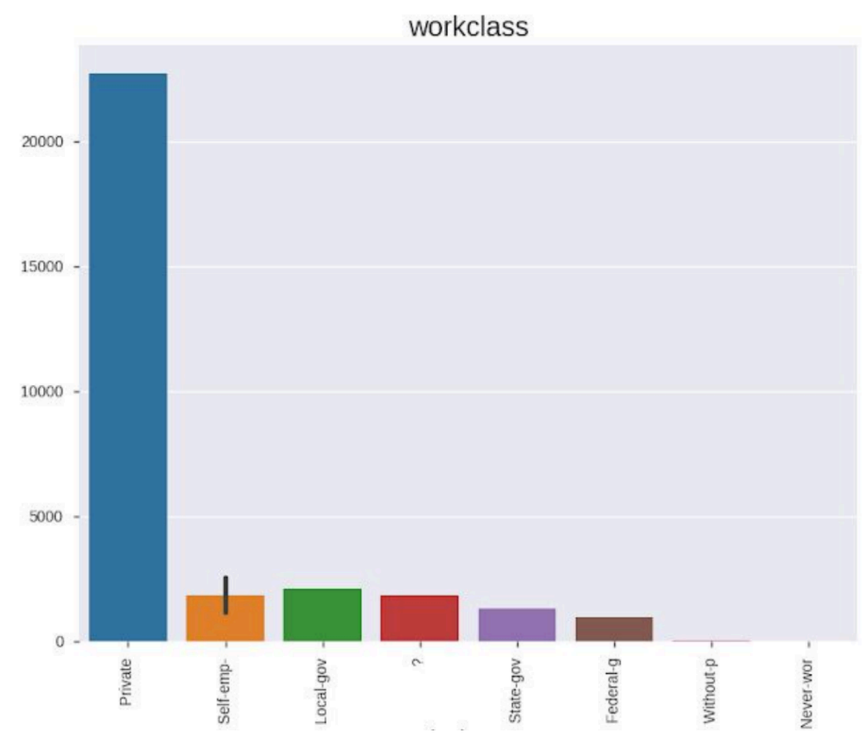


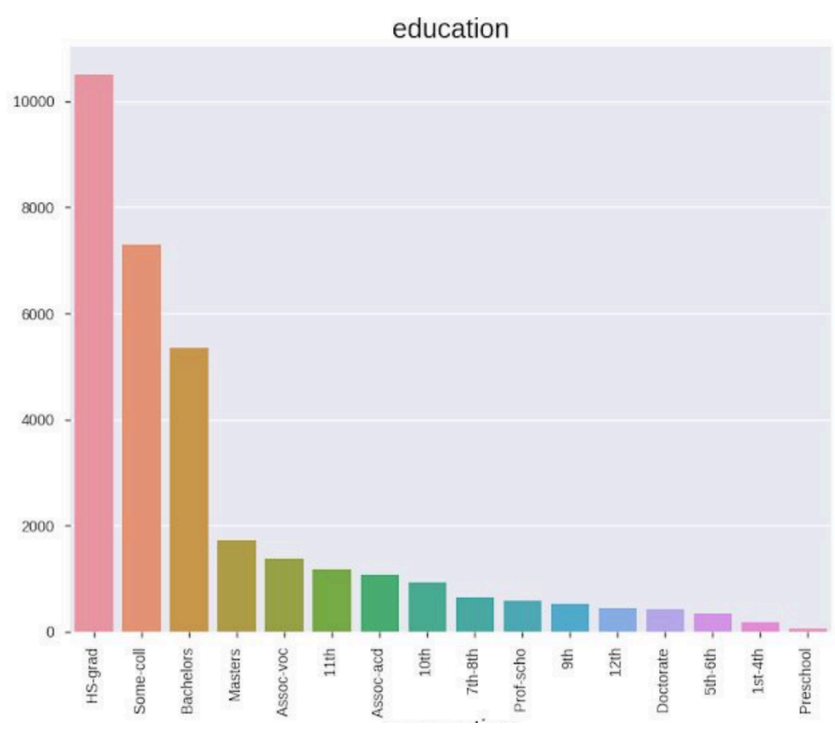


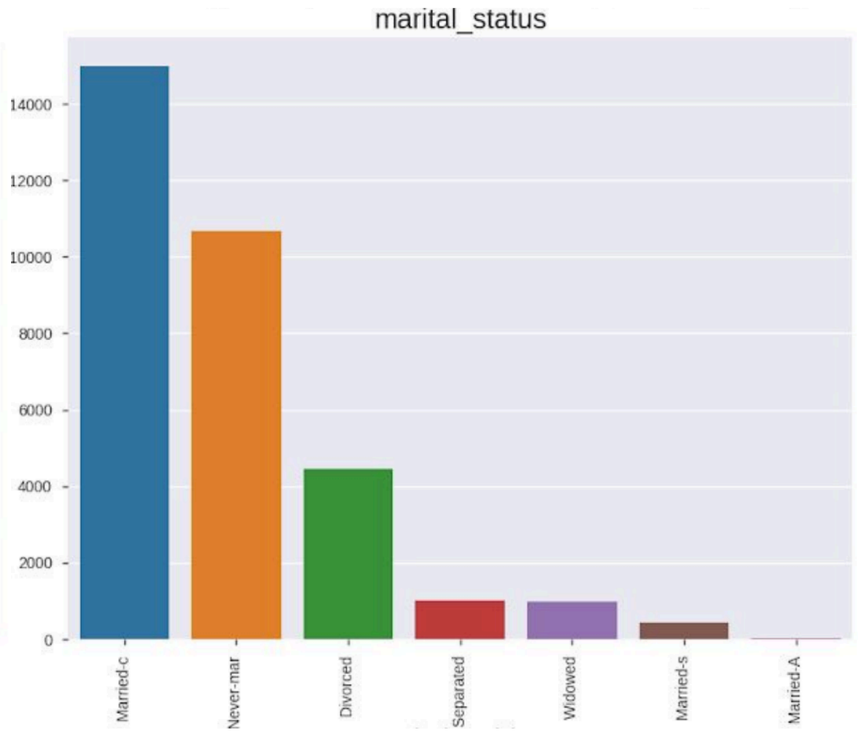


Exploratory Data Analysis

- **Descriptive** data analysis: categorical features







Exploratory Data Analysis

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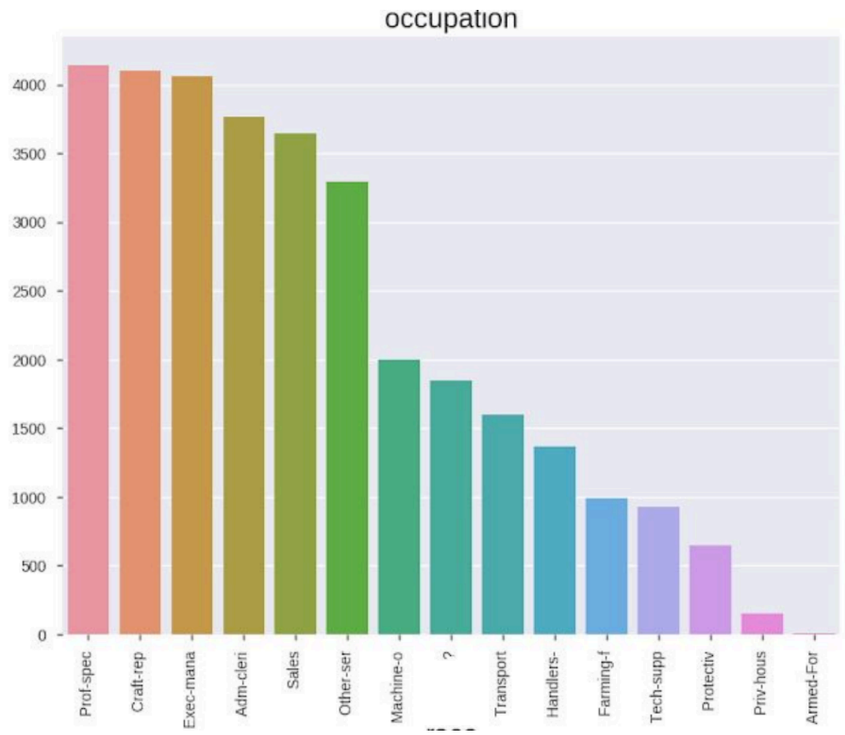

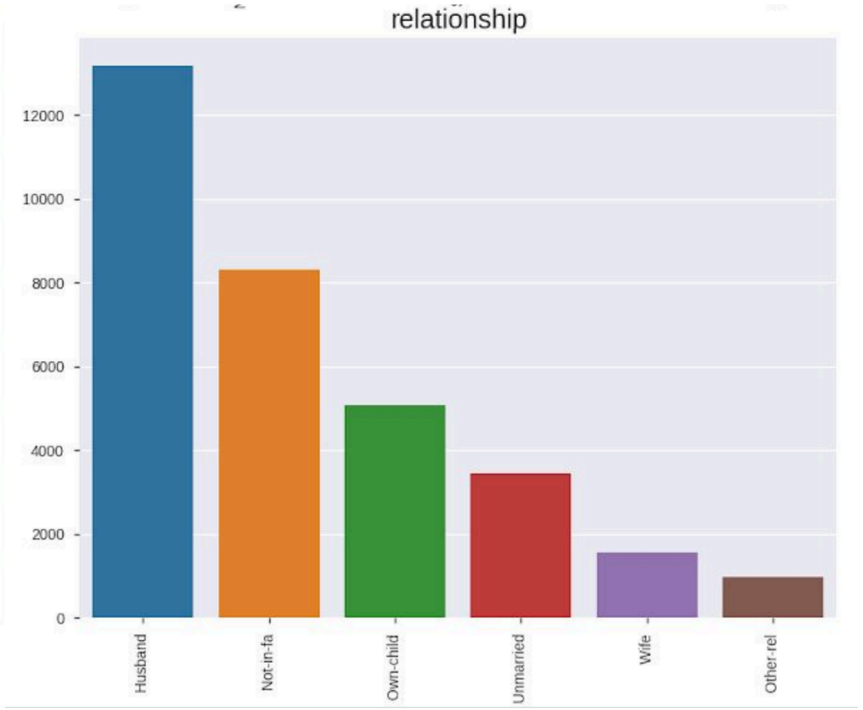

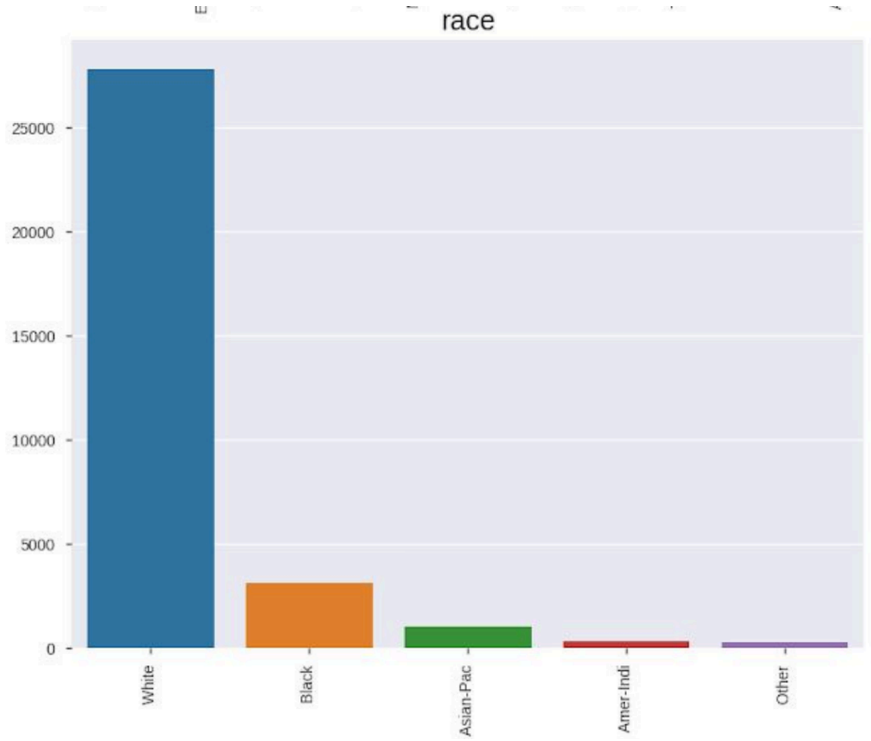

Exploratory Data Analysis

- **Correlation** analysis:

Categorical	Numerical	f-statistic	p-value
income_bracket	age	1886.707314	0.00E+00
income_bracket	functional_weight	2.915594	8.77E-02
income_bracket	education_num	4120.09578	0.00E+00
income_bracket	capital_gain	1709.150064	0.00E+00
income_bracket	capital_loss	754.830452	2.69E-164
income_bracket	hours_per_week	1813.386282	0.00E+00

Most of the numerical features are correlated with the target variable, except for functional_weight ($p > 0.05$)

cat1	cat2	chi_statistic	p_value	DoF
workclass	income_bracket	1045.7086	1.19E-210	18
education	income_bracket	4429.653302	0.00E+00	32
marital_status	income_bracket	6517.741654	0.00E+00	14
occupation	income_bracket	4031.97428	0.00E+00	30
relationship	income_bracket	6699.076897	0.00E+00	12
race	income_bracket	330.920431	4.43E-65	10
sex	income_bracket	1518.88682	0.00E+00	4
native_country	income_bracket	317.230386	8.56E-29	84

All categorical features seem correlated with the target

Feature selection

Feature selection

- As we've seen in the previous sections, there is a very large number of feature transformations we can try for a given model

Feature selection

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- Should we just throw all these features at the model?

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*Hint: **G**arbage In, Garbage Out*

Feature selection

- We should **carefully select** our features because:

Feature selection

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    - The **more features** we use in a model, the **more complex** it is. Remember: as the model's **complexity** increases, so does its **variance** and so does its tendency to **overfit**, thus **decreasing its performance**

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  - The **more features** we use in a model, the **less explicable/interpretable** it is
  - The **more features** we use in a model, the **longer** it takes to train it
  - Simply because sometimes, **less is more**

Feature selection

- Feature selection helps achieving: **Less complexity, less overfitting, more accuracy, more interpretability and faster trainings**

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  - Iterative subset selection methods (forward, backward, …)

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- To do so, we can use:
  - Filter methods
  - Iterative subset selection methods (forward, backward, …)
  - Shrinkage methods (mainly lasso regularization, ridge regularization, …)

Feature selection

- **Filter methods**: choose features based on their score in various statistical tests for their **correlation** with the target variable

Feature selection

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	Continuous Target	Categorical Target
Continuous Feature	Pearson's Correlation	LDA
Categorical Feature	Anova	Chi-Square

Feature selection

- **Filter methods**: choose features based on their score in various statistical tests for their **correlation** with the target variable

	Continuous Target	Categorical Target
Continuous Feature	Pearson's Correlation	LDA
Categorical Feature	Anova	Chi-Square

- **Pearson's correlation**: used as a measure of quantifying linear dependence between two variables
- **LDA**: Linear Discriminant Analysis used to find a linear combination of features that characterizes two or more classes
- **Anova**: (Analysis of Variance) A statistical test of wether the means of several classes are equal or not
- **Chi-Square**: used to determine wether a relationship between 2 categorical variables is likely to reflect a real association

Feature selection

- **Iterative subset selection** methods

Feature selection

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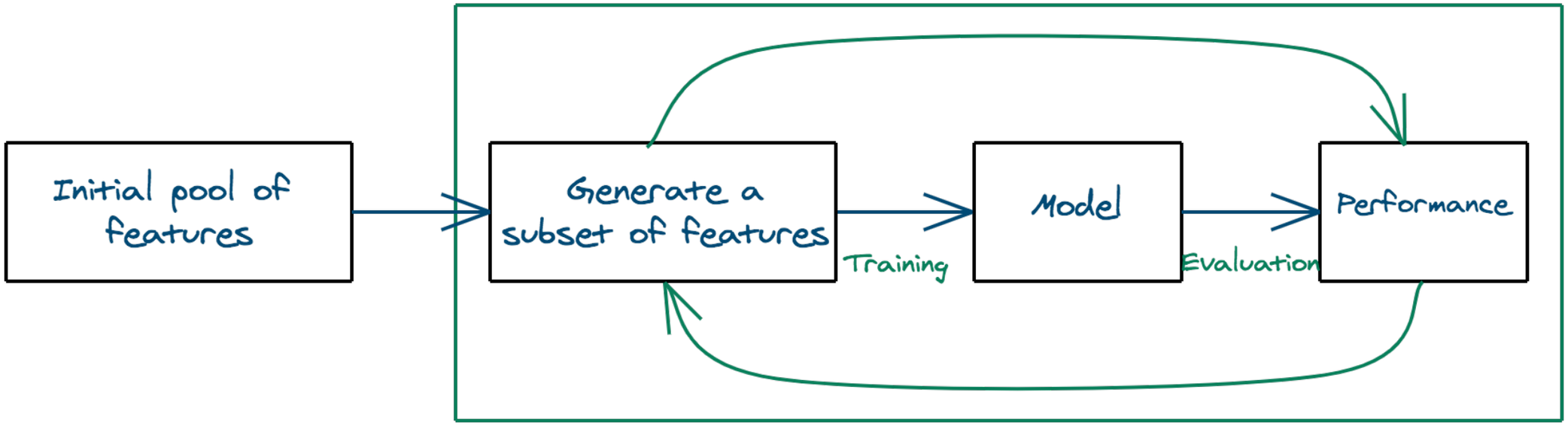
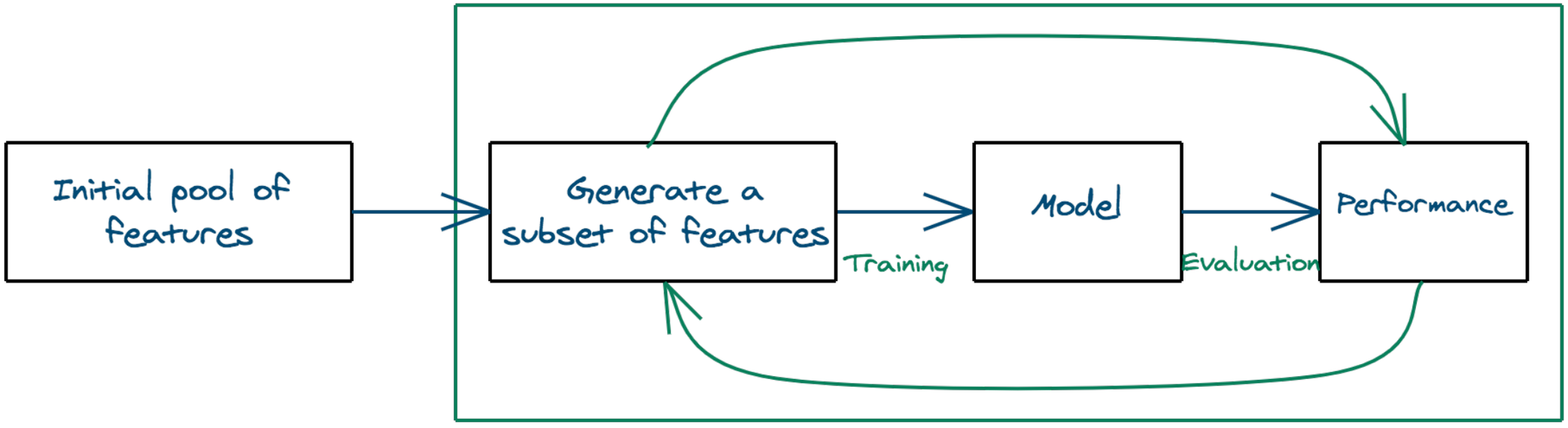


Feature selection

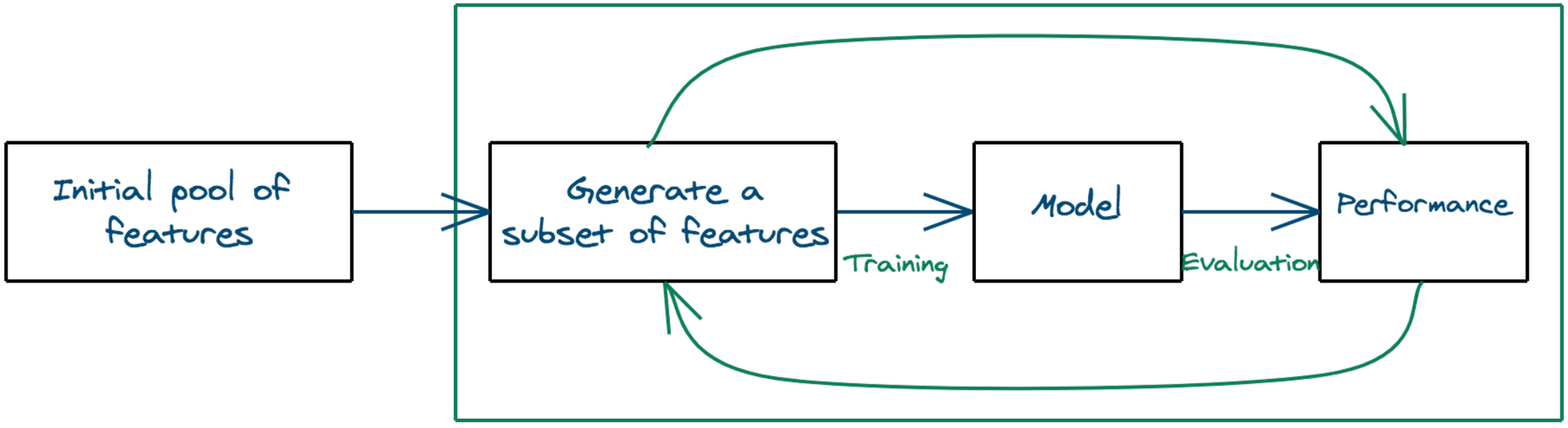
- **Iterative subset selection** methods



- To generate subsets of features, we can either employ:

Feature selection

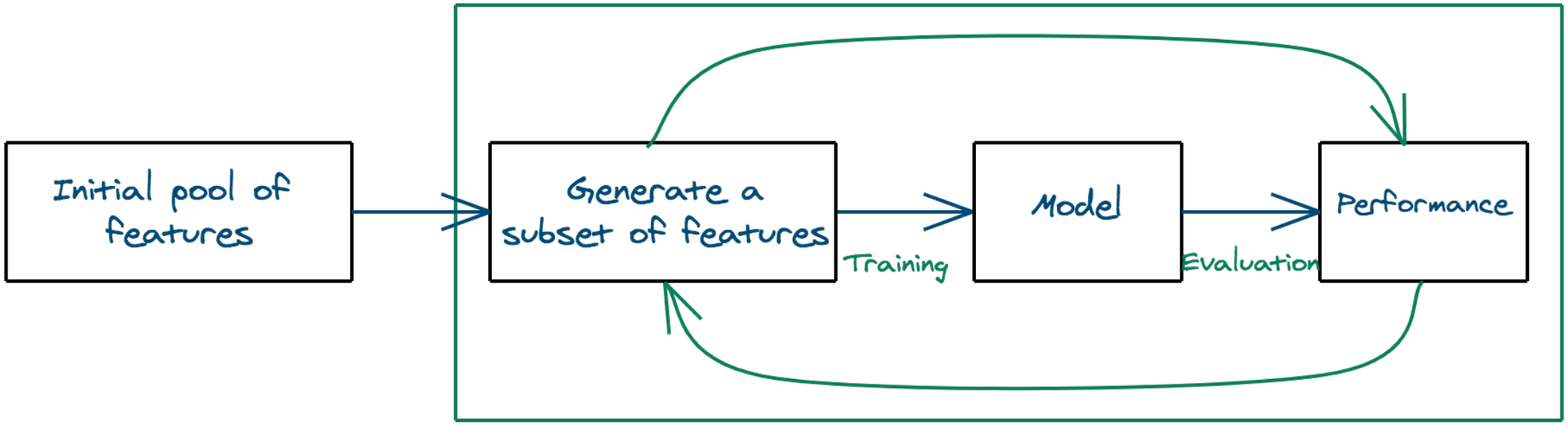
- **Iterative subset selection** methods



- To generate subsets of features, we can either employ:
  - **Forward** selection

Feature selection

- **Iterative subset selection** methods



- To generate subsets of features, we can either employ:
  - **Forward** selection
  - **Backward** Selection

Feature selection

- **Forward** selection:

Feature selection

- **Forward** selection:
  - Start with 0 features, only an intercept

Feature selection

- **Forward** selection:
  - Start with 0 features, only an intercept
  - At each iteration, we **add the feature that yields the best improvement** of the model

Feature selection

- **Forward** selection:
  - Start with 0 features, only an intercept
  - At each iteration, we **add the feature that yields the best improvement** of the model
  - We **repeat** that until **no improvement** is observed

Feature selection

- **Backward** selection:

Feature selection

- **Backward** selection:
  - Start with **all the features**

Feature selection

- **Backward** selection:
  - Start with **all the features**
  - At each iteration, we **drop the feature** whose removal yields the **best improvement** of the model

Feature selection

- **Backward** selection:
  - Start with **all the features**
  - At each iteration, we **drop the feature** whose removal yields the **best improvement** of the model
  - We **repeat** that until **no improvement** is observed