Fundamentals of Machine Learning
Lecture 6 – Feature Engineering

ML Instructional Team

April 22, 2020

Introduction

- In Machine Learning models we have seen, features are represented by fixed-size vectors.
- However, in practical Machine Learning problems, data are not always ready in this form.
- For example, in Computer Vision, images are in different sizes and therefore, without further processing, will be represented as matrices with different dimensions.
- For a face recognition problem, we will have to do object detection to extract the face in a photo and a lot more processing before the data can be used as features.
- In NLP (Natural Language Processing), texts can have different lengths, and we need to employ various techniques (E.g bag-of-words, tf-idf, word-to-vec etc.) to extract features.

Unstructured, Semi-structured, and Structured Data

- Unstructured data is data that is not in a uniform format. E.g.: text, images, videos, and audio data.
- Semi-structured data that has some semantic tags, but is not consistent or standardized. E.g. JSON, XML, csv data
- Structured data is well organized and standardized. E.g. Relational DB

Feature Engineering Overview

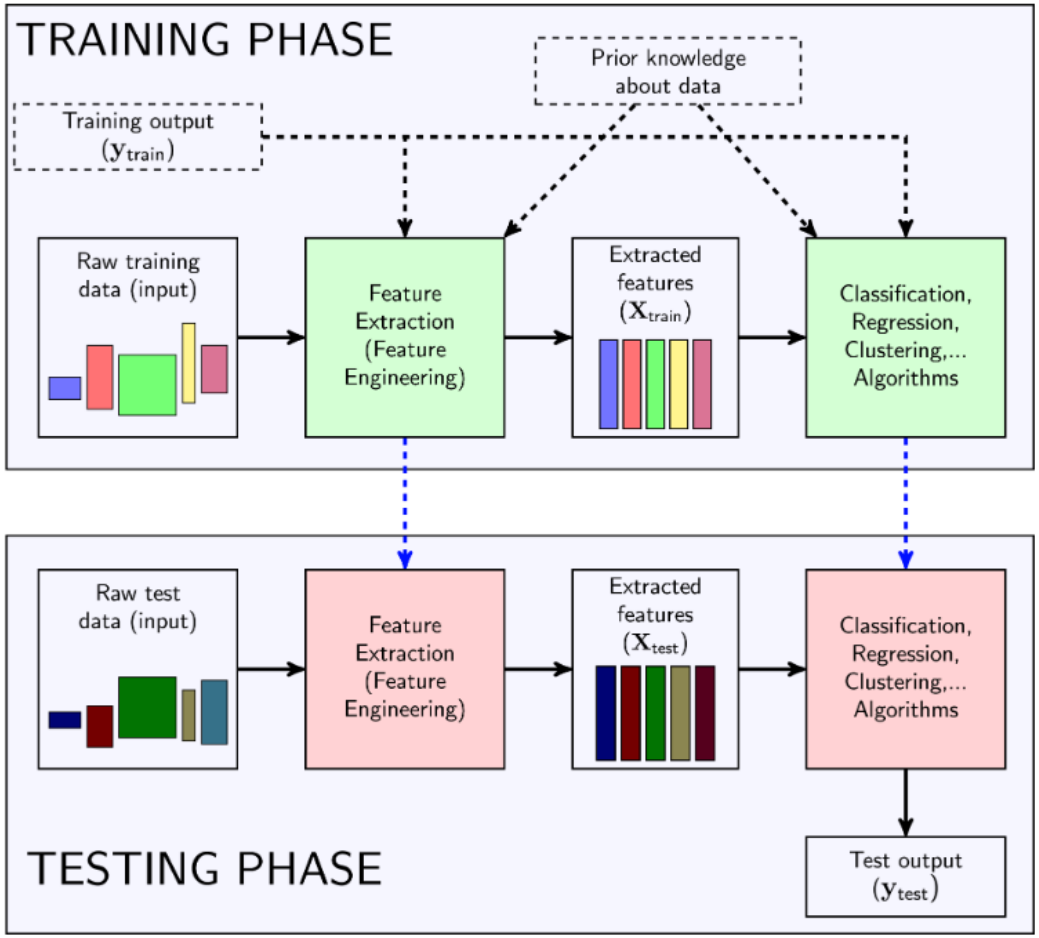

Figure: A standard machine learning pipeline (source: Machine Learning Co Ban, Vu Huu Tiep)

Data Overview

Problem Statement: Based on daily grab usage data, can we predict income of a customer, namely over or under 10 million VND per month?

	user_id	birthday	from_district	to_district	service	promo	data_time	gender	status	label
0	A	10-25-1995	1	1	car	1	2018-09-21 00:00:15	female	plantium	1
1	A	10-25-1995	1	1	car	0	2018-10-09 17:55:52	female	plantitum	1
2	B	20-04-1989	2	3	bike	0	2018-10-28 21:54:15	male	silver	1
3	C	11-18-1990	11	11	car	0	2018-10-28 01:52:27	female	gold	0
4	B	20-04-1989	2	1	car	1	2018-10-28 02:10:50	male	silver	1
5	D	15-03-1980	8	10	bike	1	2018-10-11 20:25:26	female	silver	0
6	E	27-08-1970	go_vap	go_vap	bike	0	2018-11-08 17:51:18	male	silver	0
7	F	11-12-2000	phu_nhuan	1	bike	1	2018-11-08 10:48:43	male	silver	0
8	C	11-18-1990	2	12	bike	1	2018-11-02 14:55:33	female	gold	0
9	A	10-25-1995	1	thu_duc	delivery	1	2018-11-02 22:29:04	female	plantium	1
10	D	15-03-1980	8	2	food	0	2018-09-01 10:39:23	female	silver	0
11	A	10-25-1995	1	1	food	0	2018-09-01 08:29:46	female	plantium	1
12	B	20-04-1989	2	1	car	1	2018-09-01 15:05:59	male	silver	1

What is feature engineering?

- "Coming up with features is difficult, time-consuming, requires expert knowledge. 'Applied machine learning' is basically feature engineering." — Prof. Andrew Ng.
- "Feature engineering is the process of transforming raw data into features that better represent the underlying problem to the predictive models, resulting in improved model accuracy on unseen data." — Dr. Jason Brownlee

Feature Engineering: Demo

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Feature Engineering: Demo

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- Our goal is to find features that are highly relevant to income
  1. Age of user
  2. Time using grab
  3. Most visited dictrict in working hour
  4. Total payment
  5. ...
  6. ...

Feature Engineering

- Features can come from two major types based on the raw dataset
  1. Inherent **raw features** are features that can be obtained directly from raw data without any transformation or engineering
  2. **Derived features** are features that can be obtained from feature engineering, i.e through manipulating and transforming raw data.
     For example, feature *age* is derived from *birthday* column of raw data

Different types of variable in statistics

Numerical (quantitative)

- **Discrete:** integer values, typically counts. E.g. age, sick days per year.
- **Continuous:** takes any value in a range of values. E.g. weight, height.

Categorical (qualititive)

- **Nominal:** mutually exclusive and unordered categories. E.g. sex (male/female), blood types (A/B/AB/O).
- **Ordinal:** mutually exclusive and ordered categories . E.g. disease stage (mild/moderate/severe).

Feature Engineering on Numeric Data

- Let's try out some examples of feature engineering on our numeric data

	user_id	num_usage	age
0	A	4	23
1	B	3	29
2	C	2	28
3	D	2	38
4	E	1	48
5	F	1	18

Figure: Two new features: num_usage and age derived from numeric columns

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Feature Engineering on Numeric Data

Some types of feature you might figure out

Indicator features

- thresholds: You can create an indicator variable for $age \geq 21$.
- special events: Tet, Black Friday, Christmas.

Statistics features

- the count or number of values
- mean
- standard deviation
- minimum, maximum
- 25%, 50%, and 75% percentiles

Numerical to Categorical Variable

We can transform numerical variable to categorical variable by using the following techniques: binning, ranging, percentile, threshold, etc.

Example time slot mappings. Define time slot:

- $t \in [0, 23]$: time of day.
- night: $6 \leq t$.
- working: $9 \leq t \leq 12$ and $13 \leq t \leq 17$.
- evening: $t \geq 19$.

Time slot mappings

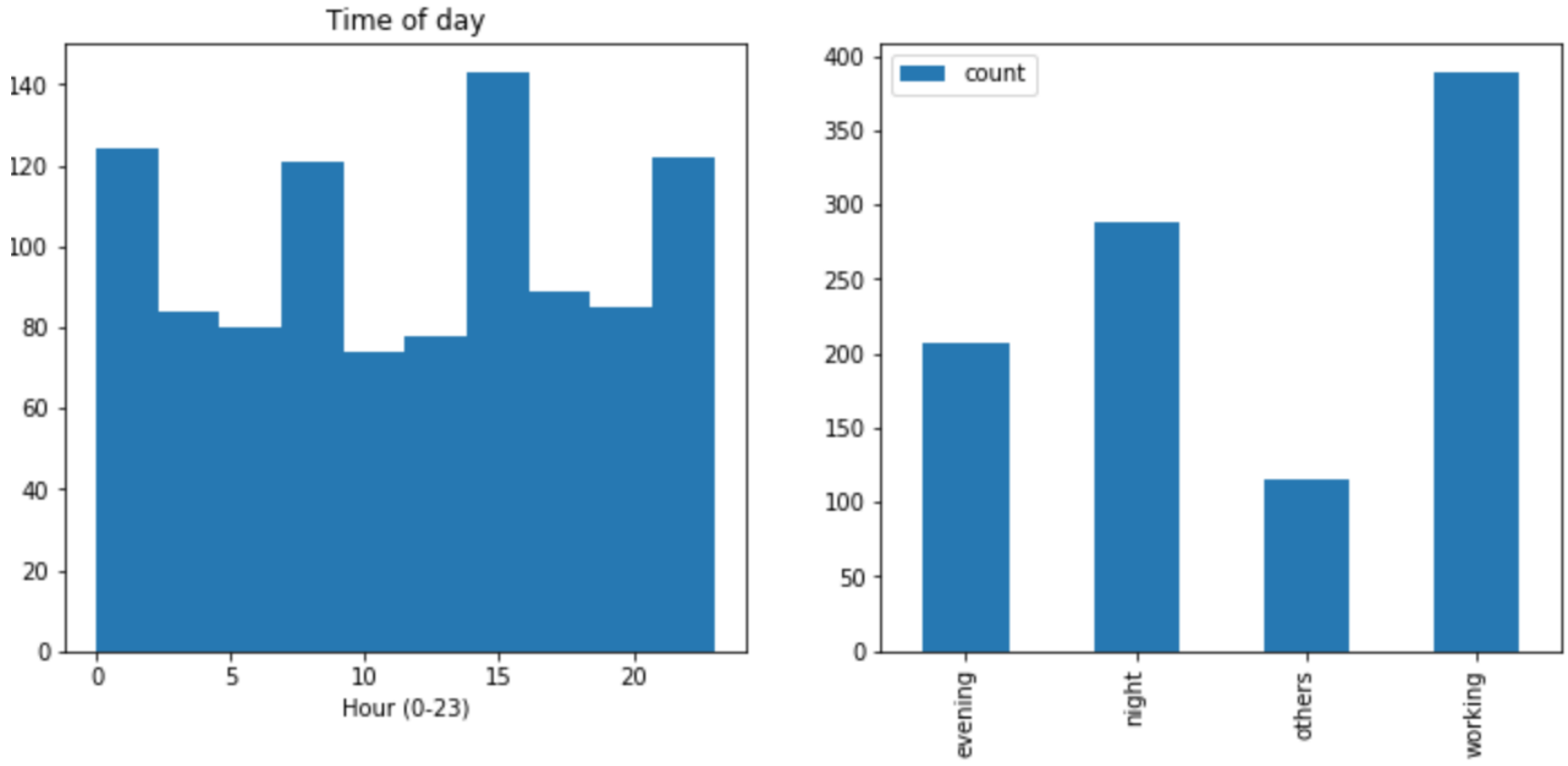

Figure: Time slot mappings from time of day

Standardizing Numerical Variables

Z-score normalization are features that are re-scaled to have a mean of zero and a standard deviation of one. By doing this, we allow models such as Gradient Descent to learn optimally and not skew towards larger scaled features (e.g. age vs income).

$$z = \frac{x - \mu}{\sigma}$$

Where:

- z: z-score.
- x: previous feature value.
- μ: mean of feature value.
- σ: standard deviation of feature value.

Z-score standardization example

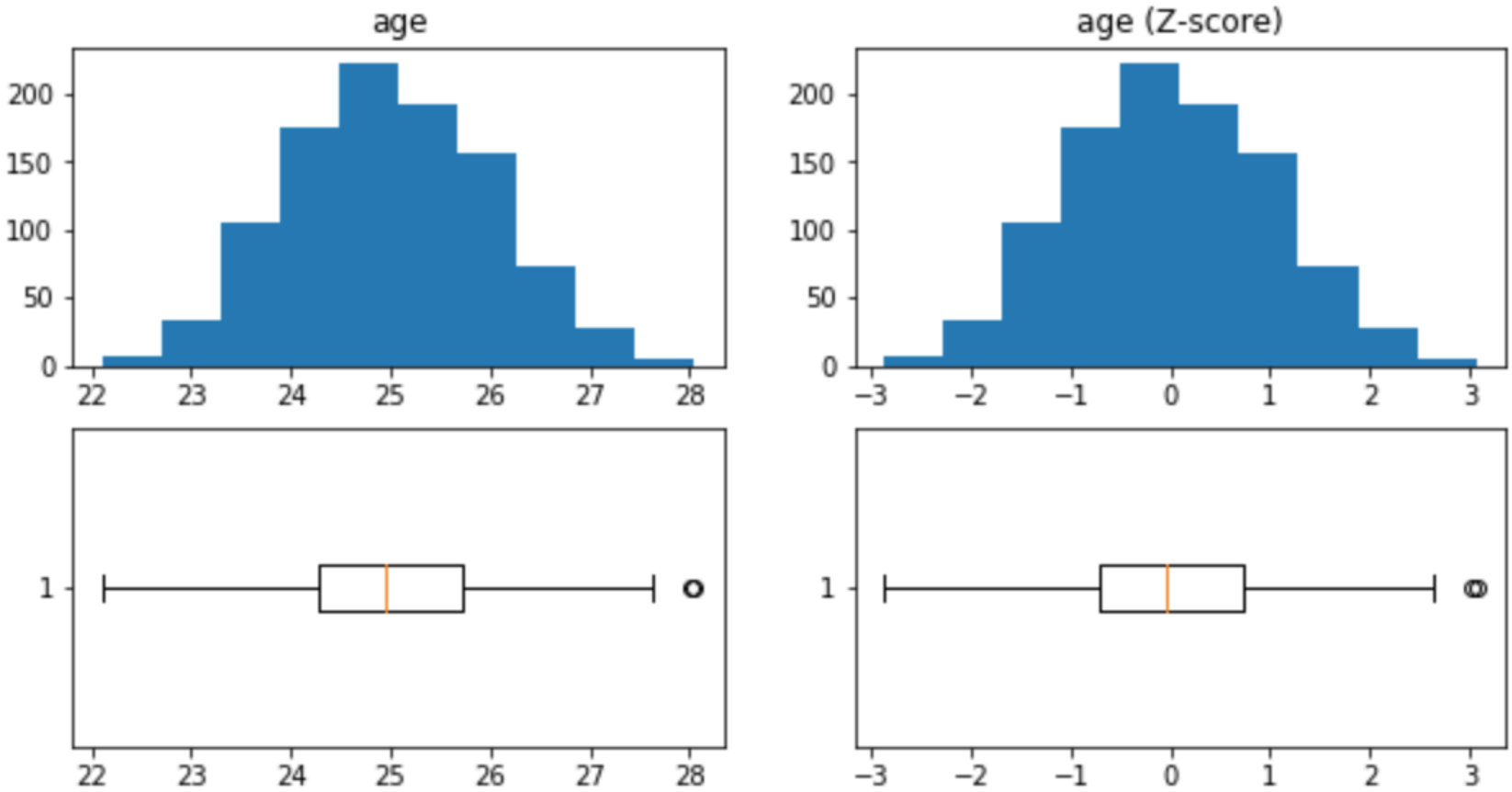

Figure: Z-score transformation on age feature

Standardizing Numerical Variables

The idea is to get every input feature into approximately a $[0, 1]$ range. The name comes from the use of min and max functions, namely the smallest and greatest values in your dataset. It requires dividing the input values by the range (i.e. the maximum value minus the minimum value) of the input variable:

$$x_i' = \frac{x_i - min(x_i)}{max(x_i) - min(x_i)}$$

Where:

- x_i: is the original i-th input value.
- x_i': normalize feature.

Min-max scaling

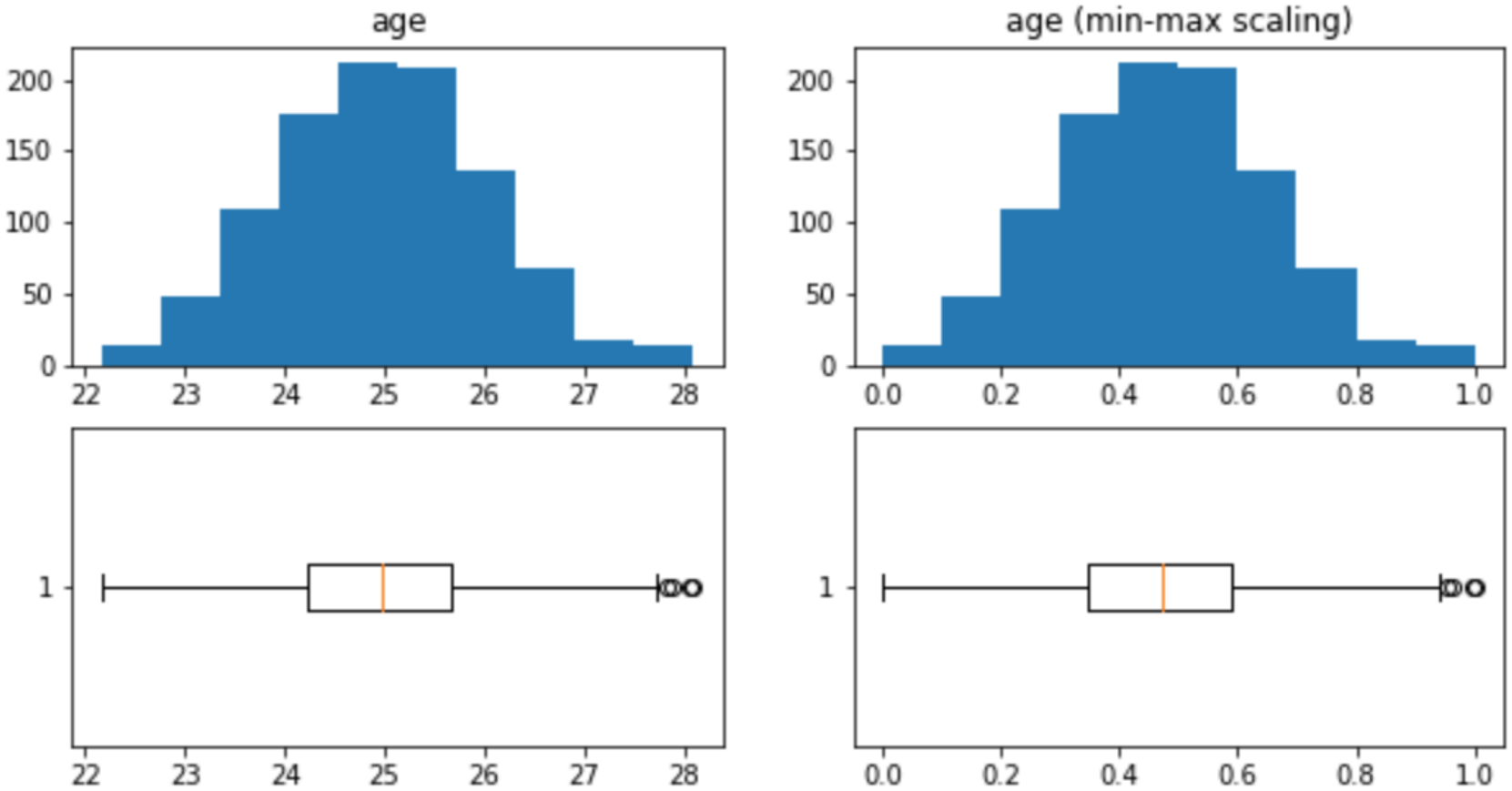

Figure: Min-Max scaling on age feature

Feature Engineering on Categorical Data

- What is the difference between nominal and ordinal features and how we can generate new features from them?
- A nominal variable is one that has two or more categories, but there is no intrinsic ordering to the categories. For example, gender (female and male) has no ordering meaning

Feature Engineering on Categorical Data

- What is the difference between nominal and ordinal features and how we can generate new features from them?
- A nominal variable is one that has two or more categories, but there is no intrinsic ordering to the categories. For example, gender (female and male) has no ordering meaning
- An ordinal variable is similar to a categorical variable. The difference between the two is that there is a clear ordering of the variables. For example, status (platinum, gold, silver) has meaning order
- Why does it matter whether a variable is categorical, or ordinal?
- How do we present information of categorical variables?

Feature Engineering on Categorical Data

- Let consider categorical columns in our dataset

	service	gender	status
0	car	female	plantium
1	car	female	plantitum
2	bike	male	silver
3	car	female	gold
4	car	male	silver
5	bike	female	silver
6	bike	male	silver
7	bike	male	silver
8	bike	female	gold
9	delivery	female	plantium
10	food	female	silver
11	food	female	plantium
12	car	male	silver

Figure: Categorical columns from grab dataset

Feature Engineering on Nominal Data

- Using **one-hot-encoding** for categorical features
- "One hot encoding is a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction" -onlineSource
- Some intuitive features: number of car/bike/food/delivery usage, status
- Basically, we will count how many times user used car, bike, food, or delivery service and represent those information in a meaningful way

Feature Engineering on Ordinal Data

- Ordinal data can be converted to numerical data and then further processed using techniques for numerical data
- How ordinal data can be converted numerical data (eg., linearly, nonlinearly) depends on the meaning of ordinal data
- For example, the letter grade (in US schools) $A, A^-, B^+, B, B^-, \ldots$ become $4.00, 3.67, 3.33, 3, 2.67, \ldots$ (linear scale)
- The status of a Grab rider can be converted to the number of points needed for that status. E.g., *Platinum* $\rightarrow$ 4500, *Gold* $\rightarrow$ 1200, *Silver* $\rightarrow$ 300, or to the median points of riders with each status.

Feature Engineering on DateTime and Coordinates

	user_id	gender_female	gender_male	bike	car	delivery	food
0	A	1	0	0.0	2.0	1.0	1.0
1	A	1	0	0.0	2.0	1.0	1.0
2	A	1	0	0.0	2.0	1.0	1.0
3	A	1	0	0.0	2.0	1.0	1.0
4	B	0	1	1.0	2.0	0.0	0.0
5	B	0	1	1.0	2.0	0.0	0.0
6	B	0	1	1.0	2.0	0.0	0.0
7	C	1	0	1.0	1.0	0.0	0.0
8	C	1	0	1.0	1.0	0.0	0.0
9	D	1	0	1.0	0.0	0.0	1.0
10	D	1	0	1.0	0.0	0.0	1.0
11	E	0	1	1.0	0.0	0.0	0.0
12	F	0	1	1.0	0.0	0.0	0.0

Figure: New features from categorical columns

References

[1] Vu Huu Tiep, Gioi thieu ve Feature Engineering, https://machinelearningcoban.com/general/2017/02/06/featureengineering/
[2] VEF Academy, Machine Learning, 2019