Feature engineering

WINNING A KAGGLE COMPETITION IN PYTHON

Yauhen Babakhin
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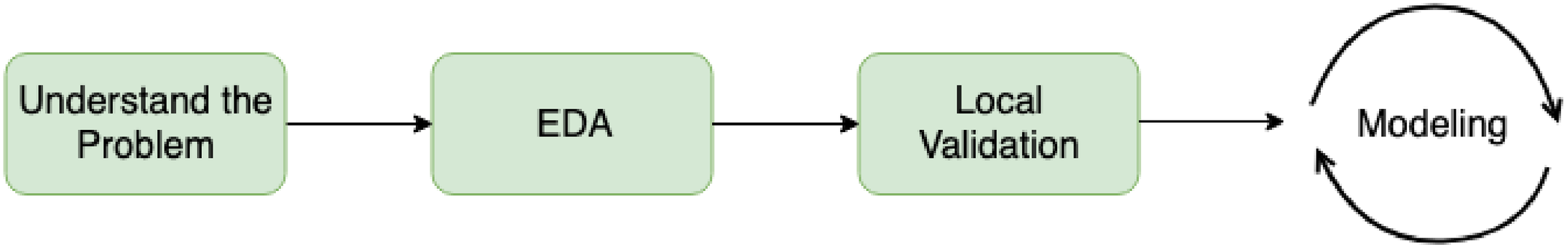
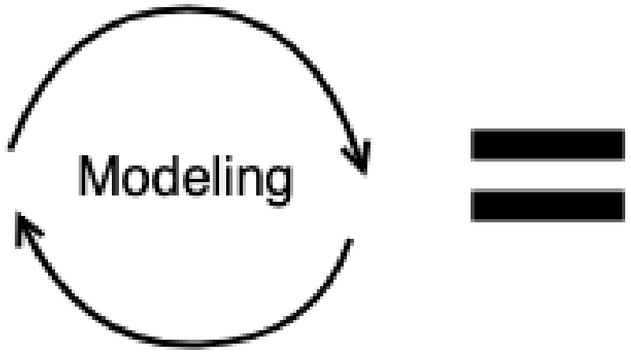
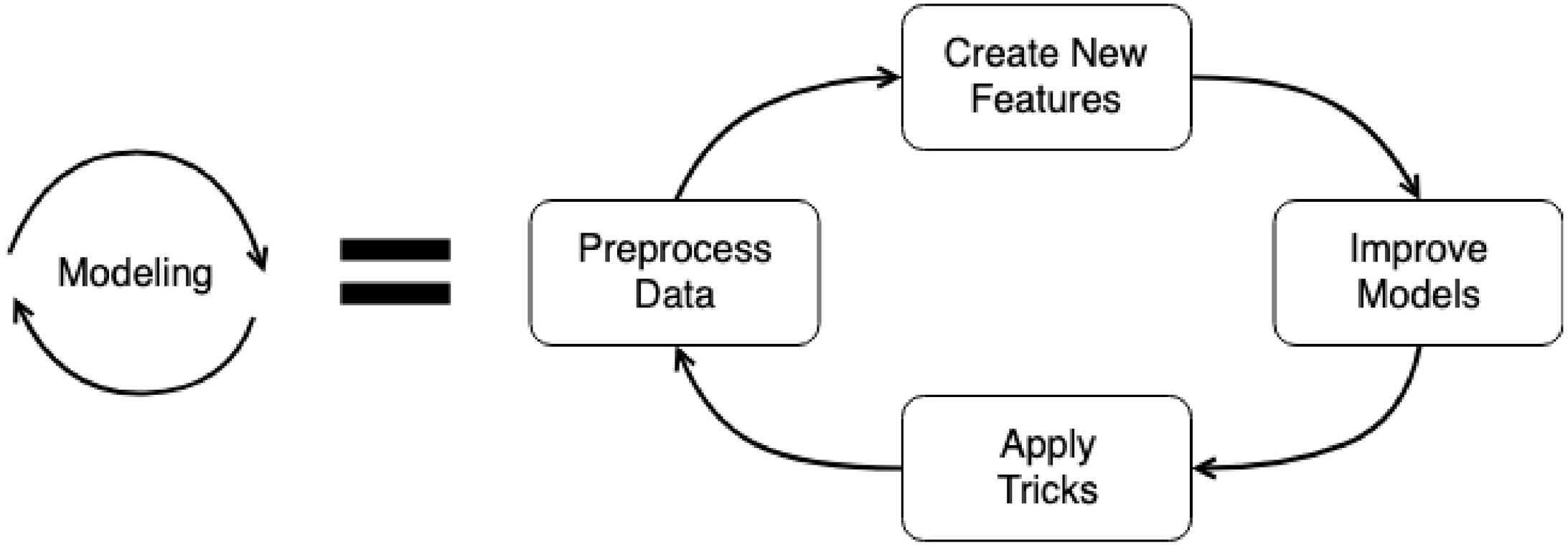
Solution workflow



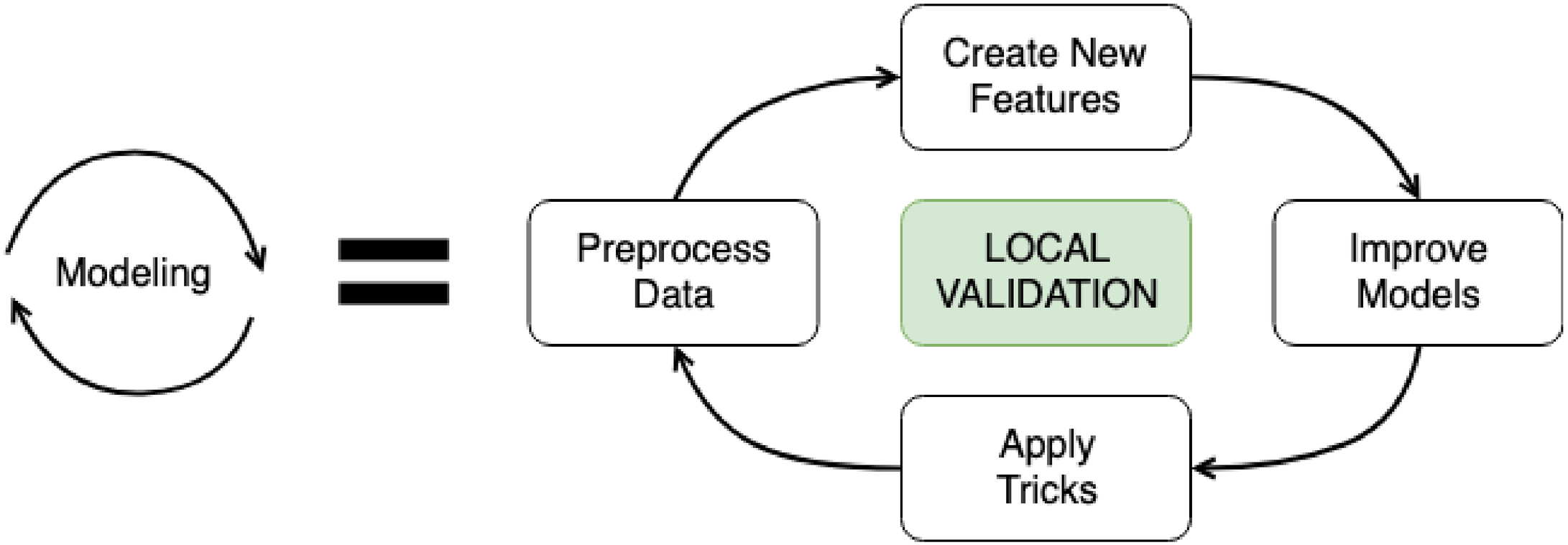
Modeling stage



Modeling stage

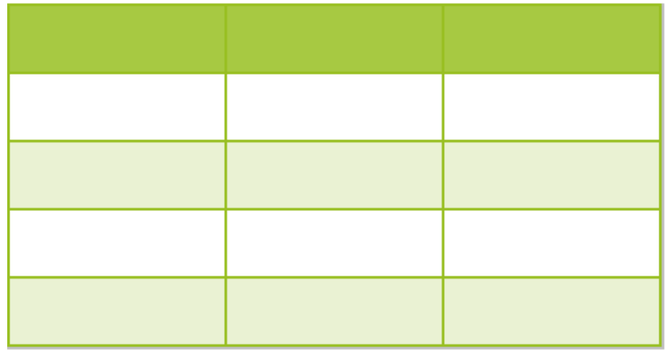


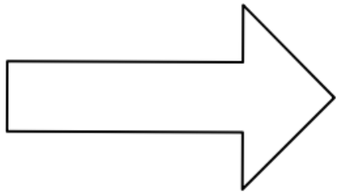
Modeling stage



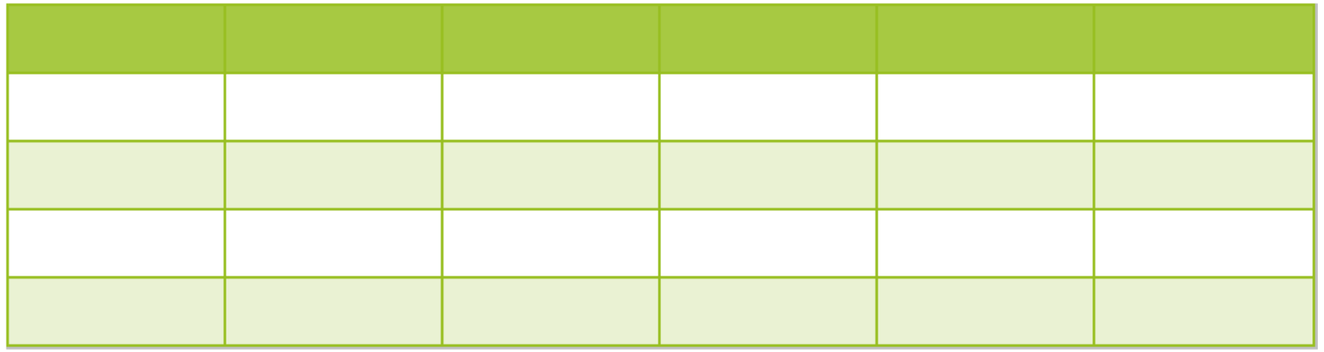
Feature engineering

Initial data



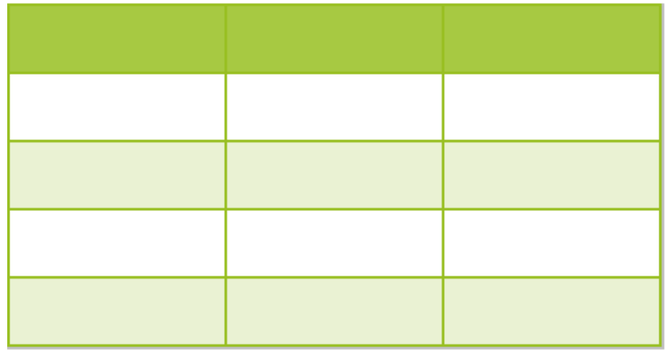


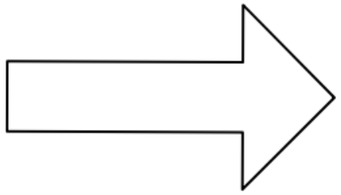
Initial data | New features



Feature engineering

Initial data

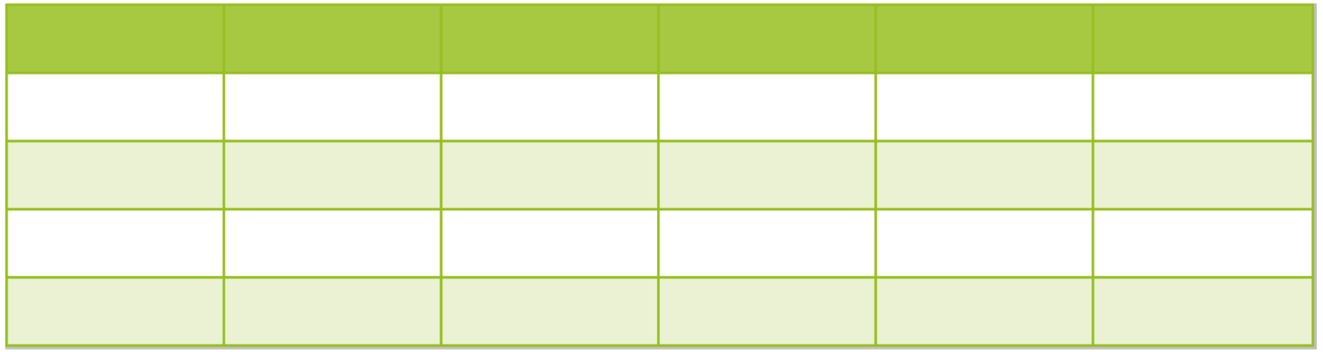




Prior experience
EDA
Domain knowledge

Initial data

New features



Feature types

- Numerical
- Categorical
- Datetime
- Coordinates
- Text
- Images

Creating features

```
# Concatenate the train and test data
data = pd.concat([train, test])
```

```
# Create new features for the data DataFrame...
```

```
# Get the train and test back
train = data[data.id.isin(train.id)]
test = data[data.id.isin(test.id)]
```

Arithmetical features

```
# Two sigma connect competition
two_sigma.head(1)
```

```
      id     bathrooms  bedrooms price interest_level
0     10     1.5        3        3000  medium
```

```
# Arithmetical features
two_sigma['price_per_bedroom'] = two_sigma.price / two_sigma.bedrooms
two_sigma['rooms_number'] = two_sigma.bedrooms + two_sigma.bathrooms
```

Datetime features

```
# Demand forecasting challenge
dem.head(1)
```

```
          id            date store  item  sales
0     100000     2017-12-01     1     1     19
```

```
# Convert date to the datetime object
dem['date'] = pd.to_datetime(dem['date'])
```

Datetime features

```
# Year features
dem['year'] = dem['date'].dt.year
# Month features
dem['month'] = dem['date'].dt.month
# Week features
dem['week'] = dem['date'].dt.weekofyear
```

date	year	month	week
2017-12-01	2017	12	48
2017-12-02	2017	12	48
2017-12-03	2017	12	48
2017-12-04	2017	12	49

```
# Day features
dem['dayofyear'] = dem['date'].dt.dayofyear
dem['dayofmonth'] = dem['date'].dt.day
dem['dayofweek'] = dem['date'].dt.dayofweek
```

date	dayofyear	dayofmonth	dayofweek
2017-12-01	335	1	4
2017-12-02	336	2	5
2017-12-03	337	3	6
2017-12-04	338	4	0

Let's practice!

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Categorical features

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Label encoding

ID	Categorical feature
1	A
2	B
3	C
4	A
5	D
6	A

ID	Label-encoded
1	0
2	1
3	2
4	0
5	3
6	0

Label encoding

```
# Import LabelEncoder
from sklearn.preprocessing import LabelEncoder
# Create a LabelEncoder object
le = LabelEncoder()
# Encode a categorical feature
df['cat_encoded'] = le.fit_transform(df['cat'])
```

```
   ID  cat  cat_encoded
0   1    A            0
1   2    B            1
2   3    C            2
3   4    A            0
```

One-Hot encoding

ID	Categorical feature
1	A
2	B
3	C
4	A
5	D
6	A

ID	Cat == A	Cat == B	Cat == C	Cat == D
1	1	0	0	0
2	0	1	0	0
3	0	0	1	0
4	1	0	0	0
5	0	0	0	1
6	1	0	0	0

One-Hot encoding

```
# Create One-Hot encoded features
ohe = pd.get_dummies(df['cat'], prefix='ohe_cat')
# Drop the initial feature
df.drop('cat', axis=1, inplace=True)
# Concatenate OHE features to the dataframe
df = pd.concat([df, ohe], axis=1)
```

```
   ID ohe_cat_A ohe_cat_B ohe_cat_C ohe_cat_D
0   1         1         0         0         0
1   2         0         1         0         0
2   3         0         0         1         0
3   4         1         0         0         0
```

Binary Features

```
# DataFrame with a binary feature
binary_feature
```

```
      binary_feat
0     Yes
1     No
```

```
le = LabelEncoder()
binary_feature['binary_encoded'] = le.fit_transform(binary_feature['binary_feat'])
```

```
  binary_feat binary_encoded
0     Yes     1
1     No      0
```

Other encoding approaches

- Backward Difference Coding
- BaseN
- Binary
- CatBoost Encoder
- Hashing
- Helmert Coding
- James-Stein Encoder
- Leave One Out
- M-estimate
- One Hot
- Ordinal
- Polynomial Coding
- Sum Coding
- Target Encoder
- Weight of Evidence

Other encoding approaches

- Backward Difference Coding
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- Sum Coding
- **Target Encoder**
- Weight of Evidence

Let's practice!

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Target encoding

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High cardinality categorical features

- Label encoder provides distinct number for each category
- One-hot encoder creates new feature for each category value
- **Target encoding to the rescue!**

Mean target encoding

Train ID	Categorical	Target
1	A	1
2	B	0
3	B	0
4	A	1
5	B	0
6	A	0
7	B	1

Test ID	Categorical	Target
10	A	?
11	A	?
12	B	?
13	A	?

Mean target encoding

1. Calculate mean on the train, apply to the test
2. Split train into K folds. Calculate mean on (K-1) folds, apply to the K-th fold
3. Add mean target encoded feature to the model

Calculate mean on the train

Train ID	Categorical	Target
1	A	1
2	B	0
3	B	0
4	A	1
5	B	0
6	A	0
7	B	1

Calculate mean on the train

Train ID	Categorical	Target
1	**A**	**1**
2	B	0
3	B	0
4	**A**	**1**
5	B	0
6	**A**	**0**
7	B	1

Calculate mean on the train

Train ID	Categorical	Target
1	A	1
2	**B**	**0**
3	**B**	**0**
4	A	1
5	**B**	**0**
6	A	0
7	**B**	**1**

Test encoding

Test ID	Categorical	Target	Mean encoded
10	A	?	0.66
11	A	?	0.66
12	B	?	0.25
13	A	?	0.66

Train encoding using out-of-fold

Train ID	Categorical	Target	Fold
1	A	1	1
2	B	0	1
3	B	0	1
4	A	1	1
5	B	0	2
6	A	0	2
7	B	1	2

Train encoding using out-of-fold

Train ID	Categorical	Target	Fold	Mean encoded
1	A	1	1	
2	B	0	1	
3	B	0	1	
4	A	1	1	
5	**B**	**0**	2	
6	**A**	**0**	2	
7	**B**	**1**	2	

Train encoding using out-of-fold

Train ID	Categorical	Target	Fold	Mean encoded
1	A	1	1	0
2	B	0	1	0.5
3	B	0	1	0.5
4	A	1	1	0
5	**B**	**0**	2	
6	**A**	**0**	2	
7	**B**	**1**	2	

Train encoding using out-of-fold

Train ID	Categorical	Target	Fold	Mean encoded
1	**A**	**1**	1	0
2	**B**	**0**	1	0.5
3	**B**	**0**	1	0.5
4	**A**	**1**	1	0
5	B	0	2	
6	A	0	2	
7	B	1	2	

Train encoding using out-of-fold

Train ID	Categorical	Target	Fold	Mean encoded
1	**A**	**1**	1	0
2	**B**	**0**	1	0.5
3	**B**	**0**	1	0.5
4	**A**	**1**	1	0
5	B	0	2	0
6	A	0	2	1
7	B	1	2	0

Practical guides

Practical guides

Smoothing

$$mean\_enc_i = \frac{target\_sum_i}{n_i}$$

$$smoothed\_mean\_enc_i = \frac{target\_sum_i + \alpha * global\_mean}{n_i + \alpha}$$

$$\alpha \in [5; 10]$$

Practical guides

Smoothing

$$mean\_enc_i = \frac{target\_sum_i}{n_i}$$

$$smoothed\_mean\_enc_i = \frac{target\_sum_i + \alpha * global\_mean}{n_i + \alpha}$$

$$\alpha \in [5; 10]$$

New categories

- Fill new categories in the test data with a *global_mean*

Practical guides

Train ID	Categorical	Target
1	A	1
2	B	0
3	B	0
4	A	0
5	B	1

Test ID	Categorical	Target	Mean encoded
10	A	?	0.43
11	B	?	0.38
12	C	?	0.40

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Missing data

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Missing data

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	NaN	1
5	NaN	2.6	0
6	A	5.3	0

Impute missing data

Numerical data

- Mean/median imputation

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	NaN	1
5	NaN	2.6	0
6	A	5.3	0

Impute missing data

Numerical data

- Mean/median imputation
- Constant value imputation

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	**4.72**	1
5	NaN	2.6	0
6	A	5.3	0

Impute missing data

Numerical data

- Mean/median imputation
- Constant value imputation

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	**-999**	1
5	NaN	2.6	0
6	A	5.3	0

Impute missing data

Numerical data

- Mean/median imputation
- Constant value imputation

Categorical data

- Most frequent category imputation

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	**-999**	1
5	NaN	2.6	0
6	A	5.3	0

Impute missing data

Numerical data

- Mean/median imputation
- Constant value imputation

Categorical data

- Most frequent category imputation
- New category imputation

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	**-999**	1
5	**A**	2.6	0
6	A	5.3	0

Impute missing data

Numerical data

- Mean/median imputation
- Constant value imputation

Categorical data

- Most frequent category imputation
- New category imputation

ID	Categorical feature	Numerical feature	Binary target
1	A	5.1	1
2	B	7.2	0
3	C	3.4	0
4	A	**-999**	1
5	**MISS**	2.6	0
6	A	5.3	0

Find missing data

```
df.isnull().head(1)
```

```
      ID    cat    num  target
0  False  False  False   False
```

```
df.isnull().sum()
```

```
ID        0
cat       1
num       1
target    0
```

Numerical missing data

```
# Import SimpleImputer
from sklearn.impute import SimpleImputer
# Different types of imputers
mean_imputer = SimpleImputer(strategy='mean')
constant_imputer = SimpleImputer(strategy='constant', fill_value=-999)
# Imputation
df[['num']] = mean_imputer.fit_transform(df[['num']])
```

Categorical missing data

```
# Import SimpleImputer
from sklearn.impute import SimpleImputer

# Different types of imputers
frequent_imputer = SimpleImputer(strategy='most_frequent')
constant_imputer = SimpleImputer(strategy='constant', fill_value='MISS')
# Imputation
df[['cat']] = constant_imputer.fit_transform(df[['cat']])
```

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