

Categorical and ordinal features

Categorical

Titanic dataset

| PassengerId | Survived | Pclass | Name | | | | | |
|-------------|----------|-----------|-------|---|------------------|---------|-------|----------|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | | | | |
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | | | | |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | | | | |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | | | | |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | | | | |
| 5 | 6 | 0 | 3 | Moran, Mr. James | | | | |
| 6 | 7 | 0 | 1 | McCarthy, Mr. Timothy J | | | | |
| 7 | 8 | 0 | 3 | Palsson, Master. Gosta Leonard | | | | |
| | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
| 0 | male | 22.000000 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S |
| 1 | female | 38.000000 | 1 | 0 | PC 17599 | 71.2833 | C85 | C |
| 2 | female | 26.000000 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| 3 | female | 35.000000 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| 4 | male | 35.000000 | 0 | 0 | 373450 | 8.0500 | NaN | S |
| 5 | male | 29.699118 | 0 | 0 | 330877 | 8.4583 | NaN | Q |
| 6 | male | 54.000000 | 0 | 0 | 17463 | 51.8625 | E46 | S |
| 7 | male | 2.000000 | 3 | 1 | 349909 | 21.0750 | NaN | S |

Ordinal features

Ticket class: 1,2,3

Driver's license: A, B, C, D

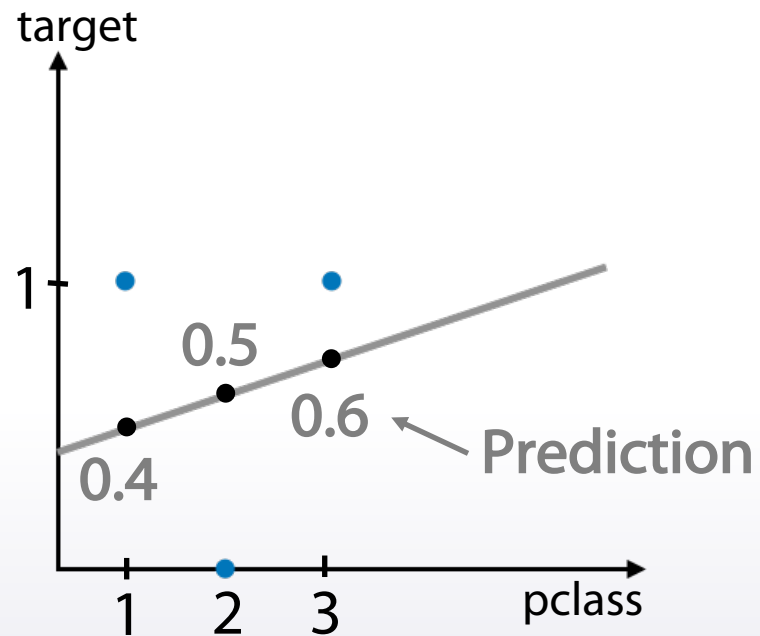
Education: kindergarden, school, undergraduate,
bachelor, master, doctoral

Label encoding

| pclass | 1 | 2 | 3 |
|--------|---|---|---|
| target | 1 | 0 | 1 |

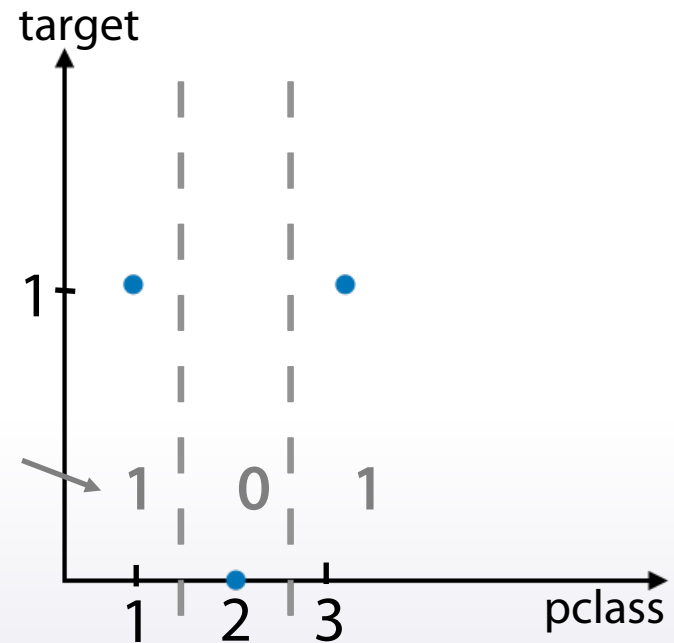
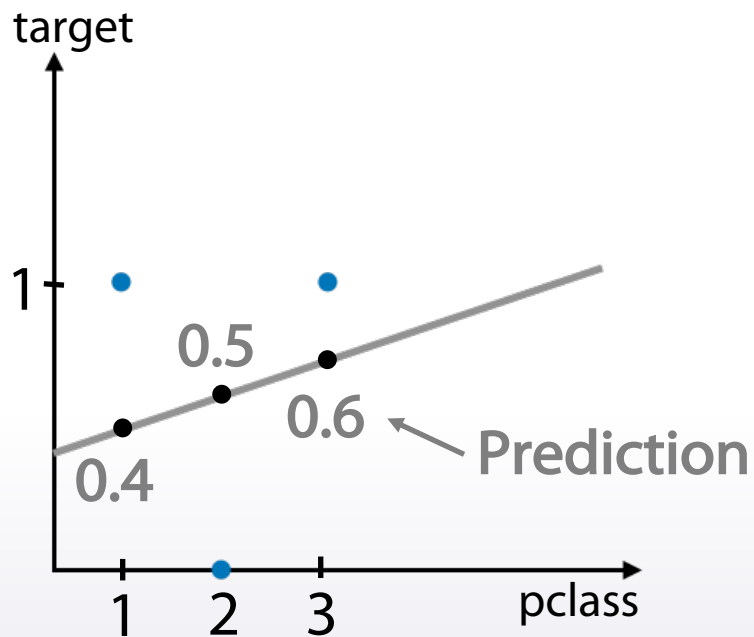
Label encoding

| pclass | 1 | 2 | 3 |
|--------|---|---|---|
| target | 1 | 0 | 1 |



Label encoding

| pclass | 1 | 2 | 3 |
|--------|---|---|---|
| target | 1 | 0 | 1 |



Label encoding

| K |
|----------|
| embarked |
| S |
| C |
| S |
| S |
| S |
| Q |
| S |
| S |
| S |
| C |
| S |
| S |

1. Alphabetical (sorted)

[S,C,Q] -> [2, 1, 3]

`sklearn.preprocessing.LabelEncoder`

2. Order of appearance

[S,C,Q] -> [1, 2, 3]

`Pandas.factorize`

Frequency encoding

| K |
|----------|
| embarked |
| S |
| C |
| S |
| S |
| S |
| Q |
| S |
| S |
| S |
| C |
| S |
| S |

[S,C,Q] -> [0.5, 0.3, 0.2]

```
encoding = titanic.groupby('Embarked').size()  
encoding = encoding/len(titanic)  
titanic['enc'] = titanic.Embarked.map(encoding)
```


Frequency encoding

| K |
|----------|
| embarked |
| S |
| C |
| S |
| S |
| S |
| Q |
| S |
| S |
| S |
| C |
| S |
| S |

[S,C,Q] -> [0.5, 0.3, 0.2]

```
encoding = titanic.groupby('Embarked').size()  
encoding = encoding/len(titanic)  
titanic['enc'] = titanic.Embarked.map(encoding)  
  
from scipy.stats import rankdata
```

Categorical features

So here, for each unique value of Pclass feature, we just created a new column. As I said, this works well for linear methods, kNN, or neural networks. Furthermore, one-hot encoding feature is already scaled because minimum this feature is zero, and maximum is one. Note that if you care for a few important numeric features, and hundreds of binary features are used by one-hot encoding, it could become difficult for tree-methods they use first ones efficiently.

One-hot encoding

| pclass | | pclass==1 | pclass==2 | pclass==3 |
|--------|--|-----------|-----------|-----------|
| 1 | | 1 | | |
| 2 | | | 1 | |
| 1 | | 1 | | |
| 3 | | | | 1 |

`pandas.get_dummies`, `sklearn.preprocessing.OneHotEncoder`

Sparse matrices are often useful when they work with categorical features or text data. Most of the popular libraries can work with these sparse matrices directly namely, XGBoost, LightGBM, sklearn, and others.

Categorical features

Feature Generation

| pclass | sex | pclass_sex |
|--------|--------|------------|
| 3 | male | 3male |
| 1 | female | 1female |
| 3 | female | 3female |
| 1 | female | 1female |



| Pclass_sex== | | | | | |
|--------------|---------|-------|---------|-------|---------|
| 1male | 1female | 2male | 2female | 3male | 3female |
| | | | | 1 | |
| | 1 | | | | |
| | | | | | 1 |
| | 1 | | | | |

Categorical features

1. Values in ordinal features are sorted in some meaningful order
2. Label encoding maps categories to numbers
3. Frequency encoding maps categories to their frequencies
4. Label and Frequency encodings are often used for tree-based models
5. One-hot encoding is often used for non-tree-based models
6. Interactions of categorical features can help linear models and KNN