Data Mining Toolkits in Python

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Contents

Overview

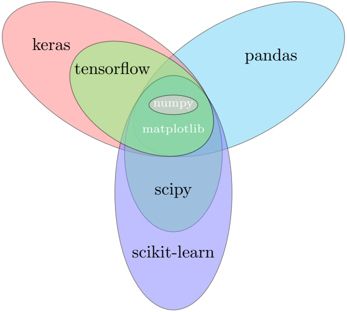

Figure: Click Figure to view popular APIs for data mining.

- **numpy** linear algebra algorithm library, operations on the n-dimensional array.
- **matplotlib** data visualization.
- **pandas** data structures and operations for manipulating tables.
- **scipy** optimization, interpolation, statistic, sparse matrix.
- **scikit-learn** Preprocessing, Clustering, Classification, Regression
- **tensorflow** Parallel Computing.
- **keras** Deep Learning.

Contents

Titanic - Machine Learning from Disaster

This is a classical data set in Kaggle, it consists of

train.csv
: This table contains all the training data(features and labels).

test.csv
: This table contains the feature attributes of the testing data.

gender_submission.csv
: This table contains the label attributes of the testing data.

While using python data mining toolkits, we do not have to know the exact meaning of each attribute or the background of the dataset, because the preprocessing and data visualization can help us parse the attributes.

Contents

Read dataset and parse attributes

When we already obtain the dataset, the first step is reading the dataset to the RAM.

```
train = pd.read_csv("datasets/train.csv")
```

Combining data from two or more tables, based on the primary key.

```
test = pd.merge(
    left=pd.read_csv("datasets/gender_submission.csv"),
    right=pd.read_csv("datasets/test.csv"),
    on="PassengerId")
```

Remark

Pandas is a hybrid of Python and SQL language. Many python-based web frameworks(ex. Django) use Pandas instead of traditional SQL operations.

It is convenient to parse all the fields by using this method

```
train.info()
```

Read dataset and parse attributes

The main usage of printing this table is to help us to work with the missing data.

```
================ Attributes Summary ================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Contents

Working with Missing Data

Filling missing values with a new class

```
train["Cabin"] = train["Cabin"].fillna("None")
```

Filling missing values with the mean value

```
train["Age"] = train["Age"].fillna(train["Age"].mean())
```

Droping samples with missing values.

```
train = train.dropna()
```

Of course, we must do the same implementation in the testing dataset. After working with the missing data, It is convenient to view the statistics by one-line command.

```
print(train.describe())
print(test.describe())
```

Working with Missing Data

The main usage of printing this table is to help us to remove the noise.

```
================ Working with Missing Data ================
       PassengerId    Survived      Pclass         Age       SibSp       Parch        Fare
count   889.000000  889.000000  889.000000  889.000000  889.000000  889.000000  889.000000
mean    446.000000    0.382452    2.311586   29.653446    0.524184    0.382452   32.096681
std     256.998173    0.486260    0.834700   12.968366    1.103705    0.806761   49.697504
min       1.000000    0.000000    1.000000    0.420000    0.000000    0.000000    0.000000
25%     224.000000    0.000000    2.000000   22.000000    0.000000    0.000000    7.895800
50%     446.000000    0.000000    3.000000   29.699118    0.000000    0.000000   14.454200
75%     668.000000    1.000000    3.000000   35.000000    1.000000    0.000000   31.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000    6.000000  512.329200
----------------------------------------------------------------
       PassengerId    Survived      Pclass         Age       SibSp       Parch        Fare
count   417.000000  417.000000  417.000000  417.000000  417.000000  417.000000  417.000000
mean   1100.635492    0.364508    2.263789   30.081832    0.448441    0.393285   35.627188
std     120.923774    0.481870    0.842077   12.563849    0.897568    0.982419   55.907576
min     892.000000    0.000000    1.000000    0.170000    0.000000    0.000000    0.000000
25%     996.000000    0.000000    1.000000   23.000000    0.000000    0.000000    7.895800
50%    1101.000000    0.000000    3.000000   29.699118    0.000000    0.000000   14.454200
75%    1205.000000    1.000000    3.000000   35.000000    1.000000    0.000000   31.500000
max    1309.000000    1.000000    3.000000   76.000000    8.000000    9.000000  512.329200
```

Contents

Noise Reduction

From the statistics above, we find that

- train["Parch"].mean() $\approx$ test["Parch"].mean()
- train["Parch"].std() $\approx$ test["Parch"].std()
- train["Parch"].max() $\sim\approx$ train["Parch"].max()

It implices that there exists noise in the attribute 'Parch'. One-line command to remove such noise.(It is equivalent to the 'where' command in SQL language)

$$\mathbf{test = test[test["Parch"] \leq 8]}$$

We also notice that $train["Fare"].std() \gg 1$, it implices that there exists noise in the attribute 'Fare'. We can use cluster algorithm to remove such noise.

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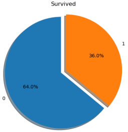
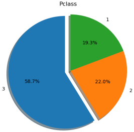
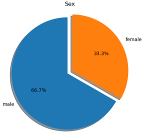
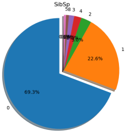
Data Visualization

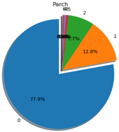
Except printing the ‘describe‘ table, we can also use data visualization to help us with data preprocessing.

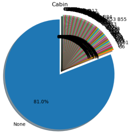


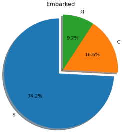


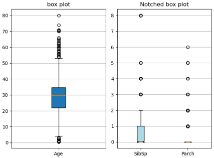


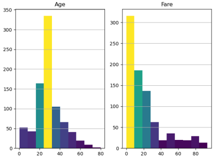












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Data Reduction

From the data visualization above, we find that the attribute ‘Cabin‘ contains too many classes, make the correlation analysis to check the validity of this attribute.

```
cross_table = pd.crosstab(train["Cabin"].values,
train["Survived"].values)
if stats.chi2_contingency(observed=cross_table.values)[1] < 0.05:
   train = train.drop(columns=["Cabin"])
   test = test.drop(columns=["Cabin"])
```

Since $p_{val} = 2.71e - 06$, we need drop this field. Check the information of the two datasets again to have a view of the attributes.

```
train.info()
test.info()
```

Data Reduction

These tables show us, the attributes contain continuous values and discrete values, so we have to convert them into the same datatype in the next step.

```
================ Data Reduction ================
<class 'pandas.core.frame.DataFrame'>
Int64Index: 836 entries, 0 to 890
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  836 non-null    int64
 1   Pclass    836 non-null    int64
 2   Sex       836 non-null    object
 3   Age       836 non-null    float64
 4   SibSp     836 non-null    int64
 5   Parch     836 non-null    int64
 6   Fare      836 non-null    float64
 7   Embarked  836 non-null    object
dtypes: float64(2), int64(4), object(2)
memory usage: 58.8+ KB
```

(a) Train

```
------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
Int64Index: 386 entries, 0 to 417
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  386 non-null    int64
 1   Pclass    386 non-null    int64
 2   Sex       386 non-null    object
 3   Age       386 non-null    float64
 4   SibSp     386 non-null    int64
 5   Parch     386 non-null    int64
 6   Fare      386 non-null    float64
 7   Embarked  386 non-null    object
dtypes: float64(2), int64(4), object(2)
memory usage: 27.1+ KB
```

(b) Test

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Partition Continuous Features into Discrete Values

By using the histogram above, the continuous variables can be binning easily.

```
train["Age"] = (train["Age"] // 16) * 16
train["Fare"] = (train["Fare"] // 19) * 19
test["Age"] = (test["Age"] // 16) * 16
test["Fare"] = (test["Fare"] // 19) * 19
```

Remark

- For different attributes, we can use different standards in binning the values. But for the same attribute in different datasets, we must obey the same rule when binning the values.
- When we using clustering methods to discrete the continuous values, we should make sure the class is sorted in order.

Now the data preprocessing is completed. Let's view these two tables

```
print(train)
print(test)
```

Data Reduction

```
=============== Discretization ===============
     Survived  Pclass     Sex   Age  SibSp  Parch  Fare Embarked
0           0       3    male  16.0      1      0   0.0        S
1           1       1  female  32.0      1      0  57.0        C
2           1       3  female  16.0      0      0   0.0        S
3           1       1  female  32.0      1      0  38.0        S
4           0       3    male  32.0      0      0   0.0        S
..        ...     ...     ...   ...    ...    ...   ...      ...
886         0       2    male  16.0      0      0   0.0        S
887         1       1  female  16.0      0      0  19.0        S
888         0       3  female  16.0      1      2  19.0        S
889         1       1    male  16.0      0      0  19.0        C
890         0       3    male  32.0      0      0   0.0        Q

[836 rows x 8 columns]
-------------------------------------------------------------
     Survived  Pclass     Sex   Age  SibSp  Parch  Fare Embarked
0           0       3    male  32.0      0      0   0.0        Q
1           1       3  female  32.0      1      0   0.0        S
2           0       2    male  48.0      0      0   0.0        Q
3           0       3    male  16.0      0      0   0.0        S
4           1       3  female  16.0      1      1   0.0        S
..        ...     ...     ...   ...    ...    ...   ...      ...
413         0       3    male  16.0      0      0   0.0        S
414         1       1  female  32.0      0      0  95.0        C
415         0       3    male  32.0      0      0   0.0        S
416         0       3    male  16.0      0      0   0.0        S
417         0       3    male  16.0      1      1  19.0        C
```

Contents

Step 1: Converting tables to n-dimensional arrays

```
train['Sex'] = train['Sex'].map('male': 0, 'female': 1).astype(int)
train['Embarked'] = train['Embarked'].map('S': 0, 'C': 1, 'Q': 2).astype(int)
x_train = train[["Pclass", "Sex", "Age", "SibSp", "Parch", "Fare", "Embarked"]].values
y_train = train["Survived"].values
```

Of course, we must do the same implementation in the testing dataset.

Step 2: Training the model

```
decision_tree = tree.DecisionTreeClassifier()
decision_tree.fit(x_train, y_train)
```

Step 3: Computing the accuracy

```
y_pred = decision_tree.predict(x_test)
print("Train accuracy: {} %".format(round(decision_tree.score(x_train, y_train) * 100, 2)))
print("Test accuracy: {} %".format(round(decision_tree.score(x_test, y_test) * 100, 2)))
```

```
================ Decision Tree ================
Train accuracy: 87.56
Test accuracy: 81.35
```

Step 4: Printing the Decision Tree

print(tree.export_text(decision_tree, feature_names=["Pclass", "Sex", "Age", "SibSp", "Parch", "Fare", "Embarked"]))

```
|--- Sex <= 0.50
|   |--- Pclass <= 1.50
|   |   |--- Fare <= 9.50
|   |   |   |--- class: 0
|   |   |--- Fare >  9.50
|   |   |   |--- Age <= 56.00
|   |   |   |   |--- Parch <= 1.50
|   |   |   |   |   |--- Fare <= 28.50
|   |   |   |   |   |   |--- Age <= 40.00
|   |   |   |   |   |   |   |--- Parch <= 0.50
|   |   |   |   |   |   |   |   |--- Age <= 24.00
|   |   |   |   |   |   |   |   |   |--- Embarked <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |   |   |   |   |--- Embarked >  0.50
|   |   |   |   |   |   |   |   |   |   |--- class: 0
```

Contents

Encoding Categorical Attributes

Before using any Neural Network to do the classification task, we have to convert the Categorical Values to vectors. The most popular encoding algorithm is one-hot. It is widely used in classification tasks.

encoder = preprocessing.OneHotEncoder()
encoder.fit(train[["Pclass", "Sex", "Embarked"]].values)

Example

The output of encoder.transform([[3, "male", "Q"], [3, "female", "S"]] is

```
================ Encoding Categorical Features ================
[[3, 'male', 'Q'], [3, 'female', 'S']] ->
 [[0. 0. 1. 0. 1. 0. 1. 0.]
 [0. 0. 1. 1. 0. 0. 0. 1.]]
```

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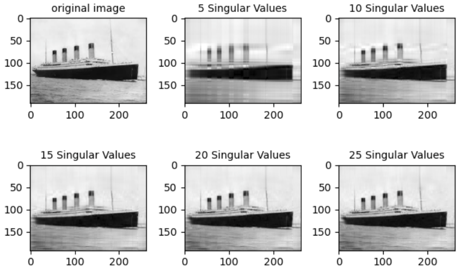
The one-hot encoder will greatly increase the dimension of features, so we can use PCA to reduce it. PCA is an SVD-based method. Its core is to remain the parts with high Singular Values which is similar to the image compression technology.



Remark

For Deep Learning, PCA is not necessary.

Contents

MLP

Step 1: Converting tables to n-dimensional arrays

```
x_train = np.concatenate([
    encoder.transform(train[["Pclass", "Sex", "Embarked"]].values).toarray(),
    train[["Age", "SibSp", "Parch", "Fare"]].values
], axis=1)
y_train = train["Survived"].values
```

Of course, we must do the same implementation in the testing dataset.

Step 2: Build the model

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.BatchNormalization(),
    tf.keras.layers.Dense(2)
])
model.compile(
    optimizer=tf.keras.optimizers.Adam(0.005),
    loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=['accuracy'])
```

MLP

Step 3: Training the model

```
model.fit(
    x_train, y_train, batch_size=4, epochs=20,
    validation_data=(x_test, y_test),
    callbacks=[
        tf.keras.callbacks.LearningRateScheduler(lambda epoch, lr: 0.75 ** (epoch // 10) * lr,
verbose=1),
        tf.keras.callbacks.TensorBoard(log_dir="logs/" +
datetime.now().strftime("%Y%m%d-%H%M%S"), histogram_freq=1)
    ],
)
```

The computer will print the training logs in the terminal

```
Epoch 1/20
Epoch 00001: LearningRateScheduler reducing learning rate to 0.004999999888241291.
209/209 [==============================] - 3s 9ms/step - loss: 0.9013 - accuracy: 0.6268 - val_loss: 0.8936 - val_accuracy: 0.6140
...
Epoch 5/20
Epoch 00005: LearningRateScheduler reducing learning rate to 0.004999999888241291.
209/209 [==============================] - 1s 7ms/step - loss: 0.6307 - accuracy: 0.6644 - val_loss: 0.3849 - val_accuracy: 0.8860
...
Epoch 9/20
Epoch 00009: LearningRateScheduler reducing learning rate to 0.004999999888241291.
209/209 [==============================] - 1s 7ms/step - loss: 0.6103 - accuracy: 0.6716 - val_loss: 0.2228 - val_accuracy: 0.9715
...
```

Step 4: Open the tensorboard to view the data plot of training logs in a web browser.

$ tensorboard –logdir logs

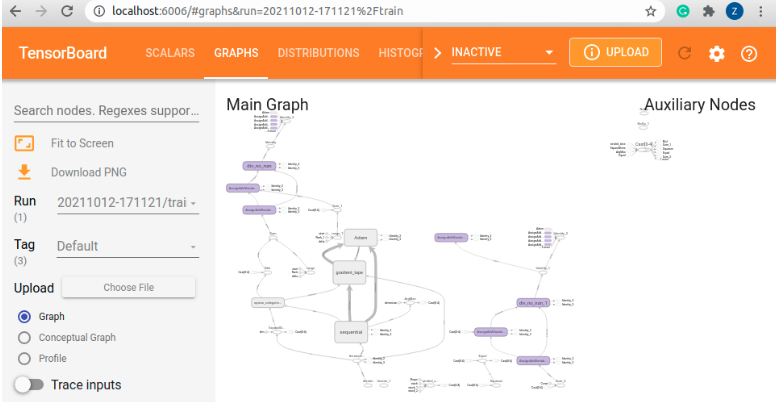


Figure: Computational Graph

Tensorboard

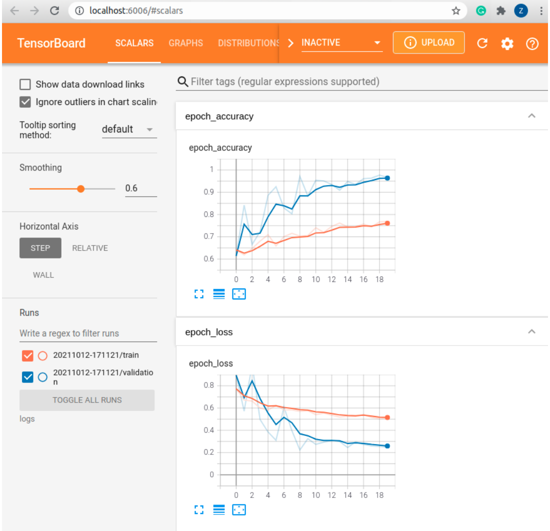


Figure: Loss and Accuracy

Tensorboard

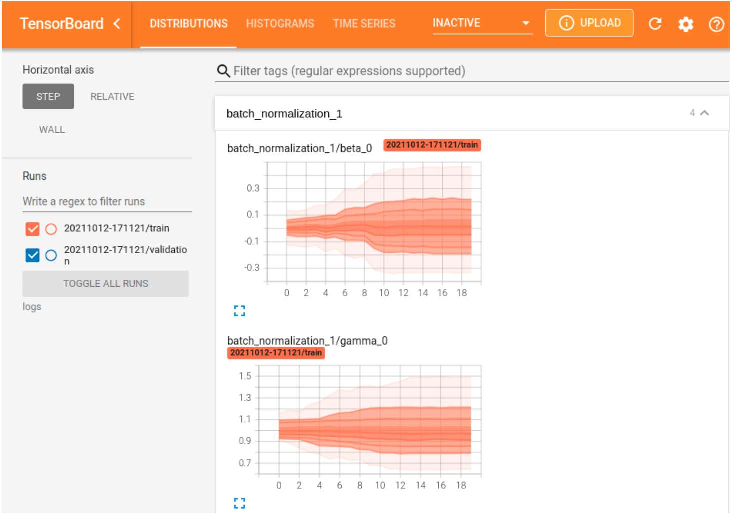


Figure: Distibutions of model parameters

Tensorboard

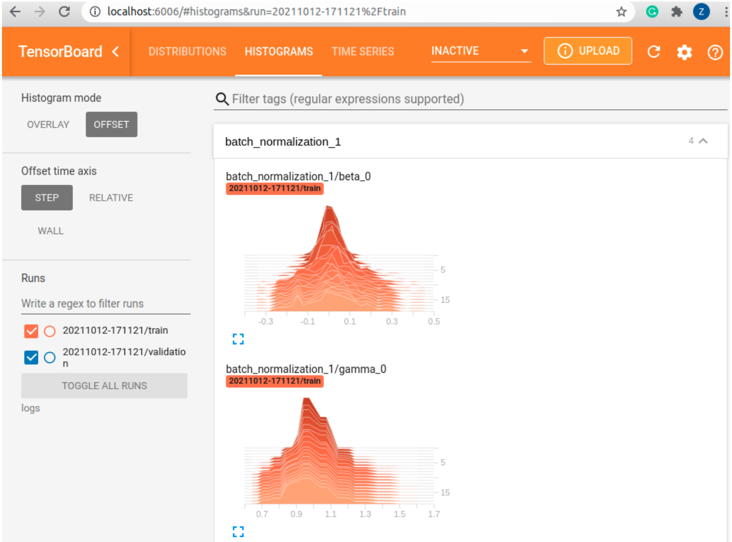


Figure: Histogram of model parameters