COMPSCI 389
Introduction to Machine Learning

Data Processing

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Data Processing

- Data collection in the real world can be challenging
- Sometimes values are logged incorrectly
    - This can be hard to catch
    - A month into a project I worked on in industry, we found a bug in the data collection code that entirely corrupted the data we had been working with (and struggling with).
- Sometimes values are not logged or cannot be collected
    - This results in **missing data**
- Sometimes values arrive in forms that are harder to deal with (e.g., text), and should be converted into values that are easier to work with (e.g., integers).
- Sometimes values are poorly scaled

Missing Data

- **Question**: What can we do if some values are missing in the data set?
  - **Example**: Some students are missing exam scores.
- **Answer 1**: Remove rows with missing values.
  - This can add bias when there is a correlation between *when* points are missing and other features/labels.
  - This can be effective when only a few rows are missing values.
- **Answer 2**: Use **imputation techniques**.
  - Replace missing values with the mean or median feature value.
  - Replace missing values with the feature values from the nearest neighbor (or k nearest neighbors).
  - Use more sophisticated techniques to estimate the missing values.

Data Balancing

- Consider predicting whether a rock is a meteorite.
- Gather data by collecting 1 million rocks, and labeling as meteorite (1) or not a meteorite (0).
- Almost all will not be meteorites!
- A classifier that predicts 0 will perform nearly optimally.
- **Idea**: “Oversample” points from the minority class, simulating having more points of that type.
  - **Method**: Duplicate rows from the minority class (meteorite) until the two classes (meteorite / not meteorite) have an equal numbers of samples.

Data Format

- Categorical values are often easier to work with as discrete numerical values.
  - Categorical values can easily be replaced with integers.
- This can cause problems with nominal features
  - **Major**: “computer science” → 0, “philosophy” → 1, “physics” → 2, “sociology” → 3, etc.
  - Let this be the j^{th} feature.
  - A linear parametric model could place a weight w_j on this feature.
  - This suggests that there is meaning to the numbers assigned to categories, since the integer values are scaled by the weight.

One Hot Encoding

- **One hot encoding** is a common strategy to avoid assigning meaning to the encoding of categorical features.
- If the feature has m possible values, it is converted into m features.
  - One column is converted into m columns.
- The value of the j^{th} new feature is 1 if the original feature took its j^{th} value, and 0 otherwise.
- Example: Original feature: “red”, “green”, “blue”
  - Three new features, “is red”, “is green”, and “is blue”
  - If “red”, the three new features have values [1, 0, 0]
  - If “green”, the three new features have values [0, 1, 0]
  - If “blue”, the three new features have values [0, 0, 1]

One Hot Encoding (Python/Pandas)

- `get_dummies(DataFrame, columns)`
  - `DataFrame`: The DataFrame with one or more categorical columns that you want to one hot encode.
  - `Columns`: The columns in the data frame that you would like to one hot encode.
  - Return value: A new data frame with one hot encodings.
- Example:

```
import pandas as pd
one_hot_encoded_df = pd.get_dummies(df, columns=['major'])
```

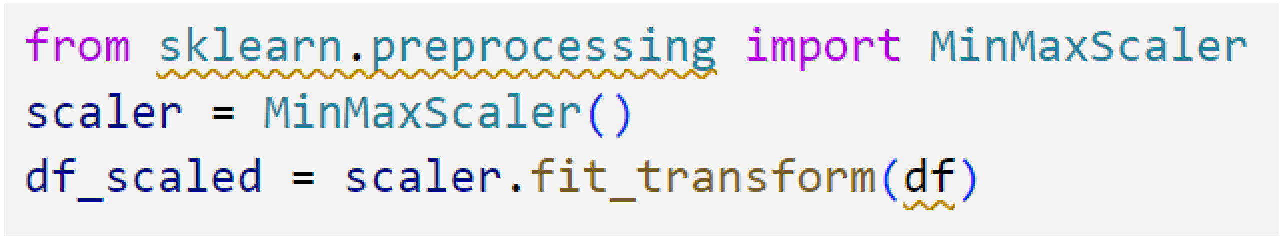
- Note: `get_dummies` returns columns with "`True`" and "`False`" rather than 1 and 0. You can obtain the numerical values with the argument `dtype=float`.

Feature Scaling

- When features have very different scales, it can cause problems for some ML algorithms.
  - **Question**: Consider a data set with income (range 0 to 1 million) and age (range 0 to 100). If we use nearest neighbor algorithms with Euclidean distance, what will happen?
  - **Answer**: Points with (relatively) slightly different incomes will be viewed as far apart relative to points with different ages.
  - **Note**: This is not unique to nearest neighbors algorithms. *Most* ML algorithms can struggle when features have very different scales.
- When all features have a very large or small scale, it can change the necessary hyperparameters in unintuitive ways.
  - **Example**: The step size for running gradient descent to fit a linear parametric model, using the second-degree polynomial basis, to the GPA data set (see `15 Data Cleaning Intro.ipynb`).

Feature Scaling

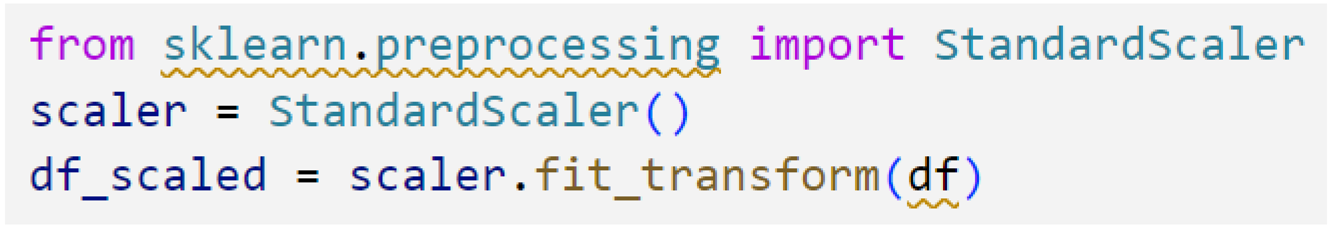
- **Idea**: Re-scale features.
- **Approach 1 (Min-Max Scaling)**: Normalize to the range [0,1]
  - $x_{\text{normalized}} = (x_{\text{unnormalized}} - \min)/(\max - \min)$
  - Scikit-learn includes “Scalers” that perform common feature rescaling.
  - The `fit_transform` function “fits” the scaler to the data (e.g., calculating min and max values of features) and then “transforms” the data (applies the specified rescaling).



```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df_scaled = scaler.fit_transform(df)
```

Feature Scaling

- **Idea**: Re-scale features.
- **Approach 2 (Standardization)**:
  - Centers the feature (so the average is zero)
  - Rescales the feature so that the standard deviation is 1
  - $x_{\text{normalized}} = (x_{\text{unnormalized}} - \text{mean})/(\text{standard deviation})$



```python
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df)
```

Feature Scaling

- There are *many* other strategies, but min-max scaling and standardization are the most common.
- Other examples:
  - Robust scaling (like standardization, but more robust to outliers)
    - `RobustScaler()`
  - Normalization (scales individual rows to have unit length)
    - `Normalizer()`
  - Max Abs Scaling (divides by `max(abs(x))`)
    - `MaxAbsScaler()`

Basis Functions

- **Note**: scikit-learn provides functions for applying the polynomial basis!

```python
from sklearn.preprocessing import PolynomialFeatures
```

```python
# Expand features into polynomial basis
poly = PolynomialFeatures(degree=polynomial_degree)
X_poly = poly.fit_transform(X_scaled)
```

See `17 Data Processing Example.ipynb`

- This performs gradient descent on the sample mean squared error, fitting a linear parametric model with the second-degree polynomial basis to the GPA data.
- By including feature scaling (standardization), it is now much easier to tune the step size!

End