Week 7.2 Assignment

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Part 1: PCA and Variance Threshold in a Linear Regression

1. Import the housing data as a data frame and ensure that the data is loaded properly.

In [ ]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.feature_selection import VarianceThreshold
from sklearn.preprocessing import MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import tree as t
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from numpy import array
```

In [ ]:
```
df = pd.read_csv('./DATA/train.csv')
df.head()
```

Out[ ]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub

5 rows × 81 columns

2. Drop the "Id" column and any features that are missing more than 40% of their values.

In [ ]:
```
# Determine columns missing  40% of their values
percent_missing = df.isnull().sum() * 100 / len(df)
missing_value_df = pd.DataFrame({'column_name': df.columns,
                                 'percent_missing': percent_missing})
missing_value_df
```

Out[ ]:

	column_name	percent_missing
MSSubClass	MSSubClass	0.0
MSZoning	MSZoning	0.0
LotFrontage	LotFrontage	0.0
LotArea	LotArea	0.0
Street	Street	0.0
...	...	...
MoSold	MoSold	0.0
YrSold	YrSold	0.0
SaleType	SaleType	0.0
SaleCondition	SaleCondition	0.0
SalePrice	SalePrice	0.0

80 rows × 2 columns

In [ ]:
```
# Drop the "Id" column
df = df.drop(['Id'], axis=1)

# Validate the transformation was successful
df.head()
```

Out[ ]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	Lc
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	

5 rows × 80 columns

In [ ]:
```
# Establish a variable for the 40% threshold
perc = 40.0

# Calculate the minimum non NaN values needed to remain in the dataset
min_count = int(((100-perc)/100)*df.shape[0])

# Remove columsn with more than 40% NaN
df = df.dropna(axis=1, thresh=min_count)

# Validate the transformation was successful
df.head()
```

Out[ ]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfi
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Insid
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR:
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Insid
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corne
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR:

5 rows × 75 columns

In [ ]:
```
df.shape
```

Out[ ]:
```
(1460, 80)
```

3. For numerical columns, fill any missing data with the median value

In [ ]:
```
numerical_columns = df.select_dtypes(include=['number']).columns

for column in numerical_columns:
    median = df[column].median()
    df[column] = df[column].fillna(median)
```

4. For categorical columns, fill in any missing data with the most common value (mode).

In [ ]:
```
cols = df.columns
categorical_columns = list(set(cols)-set(numerical_columns))
for column in categorical_columns:
    mode = df[column].mode()
    df[column] = df[column].fillna(mode)
```

5. Convert the categorical columns to dummy variables.

In [ ]:
```
df_dummies = pd.get_dummies(df, columns=categorical_columns)
df_dummies.head()
```

Out[ ]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrA
0	60	65.0	8450	7	5	2003	2003	1
1	20	80.0	9600	6	8	1976	1976	
2	60	68.0	11250	7	5	2001	2002	1
3	70	60.0	9550	7	5	1915	1970	
4	60	84.0	14260	8	5	2000	2000	3

5 rows × 289 columns

6. Split the data into a training and test set, where the SalePrice column is the target.

In [ ]:

```
# Create x & y arrays
x = df_dummies.drop('SalePrice', axis=1)
y = df_dummies['SalePrice']

# Create training & test datasets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2)
```

7. Run a linear regression and report the R2-value and RMSE on the test set.

In [ ]:

```
# Create a model
model = LinearRegression()
model.fit(x_train, y_train)

# Build predictions
test_predictions = model.predict(x_test)

# Calculate metrics
print('Test Metrics:')
print('R2', metrics.r2_score(y_test, test_predictions))
print('RMSE', metrics.mean_squared_error(y_test, test_predictions, squared=False))
```

```
Test Metrics:
R2 0.7336775561011084
RMSE 37216.40898473487
```

8. Fit and transform the training features with a PCA so that 90% of the variance is retained (see section 9.1 in the Machine Learning with Python Cookbook).

In [ ]:

```
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
pca = PCA(n_components=0.9, whiten=True)
x_train_pca = pca.fit_transform(x_train_scaled)
```

9. How many features are in the PCA-transformed matrix?

In [ ]:
```
x_train_pca.shape
```

Out[ ]:
```
(1168, 148)
```

There are 140 features

10. Transform but DO NOT fit the test features with the same PCA.

In [ ]:
```
x_test_scaled = scaler.transform(x_test)
x_test_pca = pca.transform(x_test_scaled)
```

11. Repeat step 7 with your PCA transformed data.

In [ ]:
```
# Create a model
model_pca = LinearRegression()
model_pca.fit(x_train_pca, y_train)

# Build predictions
test_predictions_pca = model_pca.predict(x_test_pca)

# Calculate metrics
print('Test Metrics:')
print('R2', metrics.r2_score(y_test, test_predictions_pca))
print('RMSE', metrics.mean_squared_error(y_test, test_predictions_pca, squared=False))
```

```
Test Metrics:
R2 0.815661917786432
RMSE 30962.64934955817
```

12. Take your original training features (from step 6) and apply a min-max scaler to them.

In [ ]:
```
minmax = MinMaxScaler()
x_train_minmax = minmax.fit_transform(x_train)
```

13. Find the min-max scaled features in your training set that have a variance above 0.1 (see Section 10.1 in the Machine Learning with Python Cookbook).

In [ ]:
```
thresholder = VarianceThreshold(threshold = 0.1)
x_train_high_var = thresholder.fit_transform(x_train_minmax)
```

14. Transform but DO NOT fit the test features with the same steps applied in steps 11 and 12.

In [ ]:
```
x_test_minmax = minmax.transform(x_test)
x_test_high_var = thresholder.transform(x_test_minmax)
```

15. Repeat step 7 with the high variance data.

In [ ]:
```
# Create a model
model_high_var = LinearRegression()
model_high_var.fit(x_train_high_var, y_train)

# Build predictions
test_predictions_high_var = model_high_var.predict(x_test_high_var)

# Calculate metrics
print('Test Metrics:')
print('R2', metrics.r2_score(y_test, test_predictions_high_var))
print('RMSE', metrics.mean_squared_error(y_test, test_predictions_high_var, squared=Fa
```

```
Test Metrics:
R2 0.6899306944813162
RMSE 44173.51616075865
```

16. Summarize your findings.

- The PCA transformation allowed the model to significantly reduce the number of features while still maintaining most of the model's performance.
- The High Variance model allowed for an even greater reduction in the number of features in the model, however the model's performance was impacted signficiantly.

Part 2: Categorical Feature Selection

1. Import the data as a data frame and ensure it is loaded correctly.

In [ ]:
```
mdf = pd.read_csv(r'./DATA/mushrooms.csv')
mdf.head()
```

Out[ ]:

	class	cap-shape	cap-surface	cap-color	bruises	odor	gill-attachment	gill-spacing	gill-size	gill-color	...	stalk-surface-below-ring	stalk-color-above-ring
0	p	x	s	n	t	p	f	c	n	k	...	s	w
1	e	x	s	y	t	a	f	c	b	k	...	s	w
2	e	b	s	w	t	l	f	c	b	n	...	s	w
3	p	x	y	w	t	p	f	c	n	n	...	s	w
4	e	x	s	g	f	n	f	w	b	k	...	s	w

5 rows × 23 columns

2. Convert the categorical features (all of them) to dummy variables.

In [ ]:
```
mdf_class = mdf['class']
mdf = mdf.drop('class', axis=1)
mdf_dummies = pd.get_dummies(mdf)
mdf_dummies.head()
```

Out[ ]:

	cap-shape_b	cap-shape_c	cap-shape_f	cap-shape_k	cap-shape_s	cap-shape_x	cap-surface_f	cap-surface_g	cap-surface_s	cap-surface_y
0	0	0	0	0	0	1	0	0	1	0
1	0	0	0	0	0	1	0	0	1	0
2	1	0	0	0	0	0	0	0	1	0
3	0	0	0	0	0	1	0	0	0	1
4	0	0	0	0	0	1	0	0	1	0

5 rows × 117 columns

3. Split the data into a training and test set.

In [ ]:
```
# create variables for x,y
mx = mdf_dummies
my = mdf_class

# Create training & test datasets
mx_train, mx_test, my_train, my_test = train_test_split(mx, my, test_size = 0.2)
```

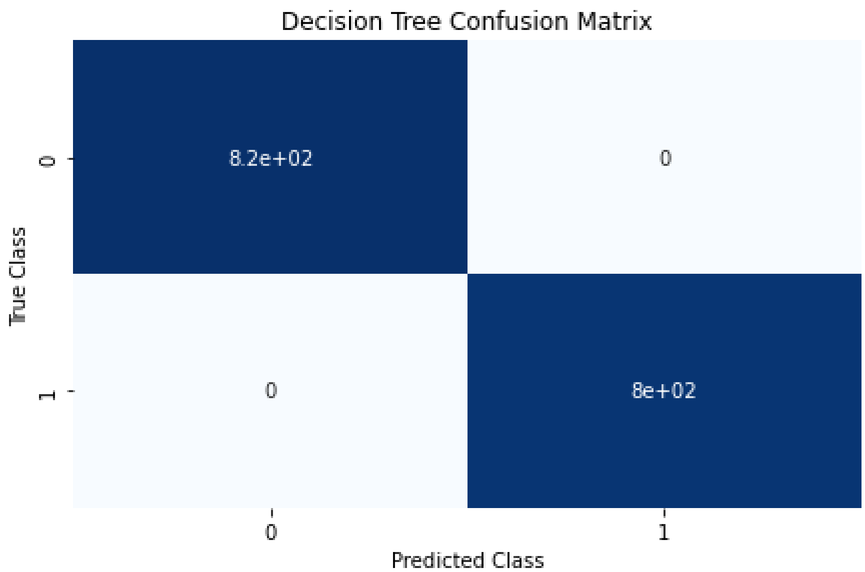
4. Fit a decision tree classifier on the training set.

In [ ]:
```
decisiontree = DecisionTreeClassifier(random_state=0)

# Train model
dt_model = decisiontree.fit(mx_train, my_train)
```

5. Report the accuracy and create a confusion matrix for the model prediction on the test set.

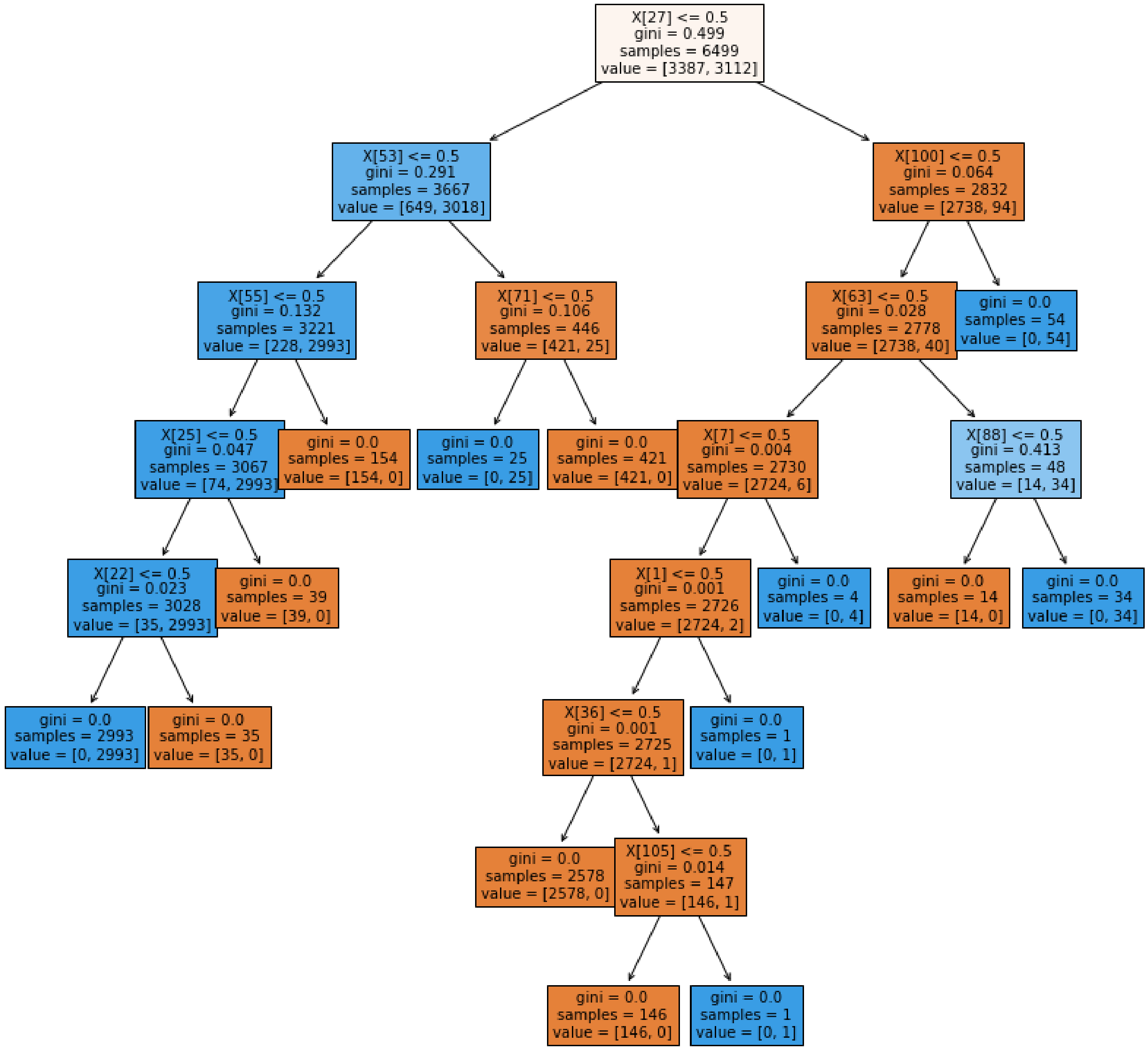
In [ ]:
```
# Build predictions
my_test_pred = dt_model.predict(mx_test)

# Calculate accuracy
accuracy_score(my_test, my_test_pred)
1.0

# Create confusion matrix
matrix = confusion_matrix(my_test, my_test_pred)

# Create pandas dataframe
c_df = pd.DataFrame(matrix)

# Create heatmap
sns.heatmap(c_df, annot=True, cbar=None, cmap="Blues")
```

```
plt.title("Decision Tree Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



6. Create a visualization of the decision tree.

In [ ]:
```
# Plot decision tree
plt.figure(figsize=(14,14))

t.plot_tree(dt_model, filled=True, fontsize=10)
plt.show()
```



7. Use a χ2-statistic selector to pick the five best features for this data (see section 10.4 of the Machine Learning with Python Cookbook).

In [ ]:
```
# Select 5 features with highest chi-squared statistics
chi2_selector = SelectKBest(chi2, k=5)
features_kbest = chi2_selector.fit_transform(mx_train, my_train)
```

8. Which five features were selected in step 7? Hint: Use the get_support function.

In [ ]:
```
# Get all features
features = array(mx_train.columns)

# Get selected features
filter = chi2_selector.get_support()
```

```
# Print Features
print(features[filter])
```

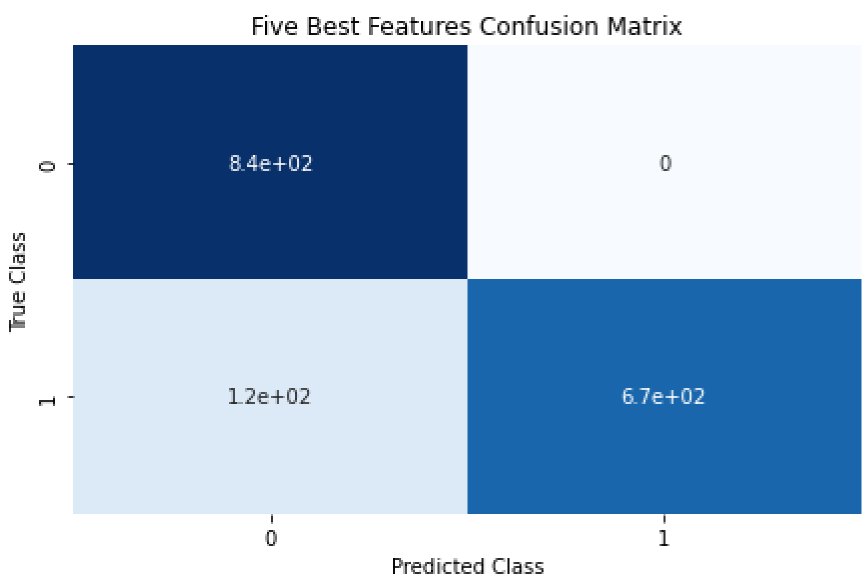
```
['odor_f' 'odor_n' 'gill-color_b' 'stalk-surface-above-ring_k'
 'stalk-surface-below-ring_k']
```

9. Repeat steps 4 and 5 with the five best features selected in step 7.

In [ ]:
```
# Creat object
decisiontree_5 = DecisionTreeClassifier(random_state=0)

# Train model
dt_5_model = decisiontree_5.fit(features_kbest, my_train)
# Fit test data
dt_5_test = chi2_selector.transform(mx_test)

# Build predictions
dt_5_test_pred = dt_5_model.predict(dt_5_test)

# Calculate accuracy
accuracy_score(my_test, dt_5_test_pred)
```

Out[ ]:
```
0.9273846153846154
```

In [ ]:
```
# Create confusion matrix
dt_5_matrix = confusion_matrix(my_test, dt_5_test_pred)

# Create pandas dataframe
c_dt5 = pd.DataFrame(dt_5_matrix)

# Create heatmap
sns.heatmap(c_dt5, annot=True, cbar=None, cmap="Blues")
plt.title("Five Best Features Confusion Matrix"), plt.tight_layout()
plt.ylabel("True Class"), plt.xlabel("Predicted Class")
plt.show()
```



10. Summarize your findings.

Using only the five best features allowed us to significantly reduce our dataset while only losing ~7% accuracy