Machine Learning 4 Construction. Data Exploration

This is a data exploration of Iris Dataset.

Main steps:

1. To check datashape description
2. To check data completeness
3. To check data balance
4. To buld some visualization to understand data structure

In [61]:
```
from sklearn.datasets import load_iris
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn import decomposition
```

1 To check datashape description

Here we load dataset and convert it into pandas DataFrame

In [64]:
```
iris_data = load_iris()
iris_data
 # convert data to Pandas DataFrame
iris_frame = pd.DataFrame(iris_data.data)

# Naming columns
iris_frame.columns = iris_data.feature_names

# Add Target column to DataFrame:
iris_frame['target'] = iris_data.target
iris_frame['name'] = iris_frame.target.apply(lambda x: iris_data.target_names[x])
iris_frame.head()
```

Out[64]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target	name
0	5.1	3.5	1.4	0.2	0	setosa
1	4.9	3.0	1.4	0.2	0	setosa
2	4.7	3.2	1.3	0.2	0	setosa
3	4.6	3.1	1.5	0.2	0	setosa
4	5.0	3.6	1.4	0.2	0	setosa

Columns are named not convinient. Let's make some renaming

In [66]:
```
iris_frame = iris_frame.rename(columns ={'sepal length (cm)':'sepal_length',
                                         'sepal width (cm)': 'sepal_width',
                                         'petal length (cm)':'petal_length',
                                         'petal width (cm)':'petal_width'})
```

In [67]:
```
iris_frame.dtypes
```

Out[67]:
```
sepal_length    float64
sepal_width     float64
petal_length    float64
petal_width     float64
target            int32
name             object
dtype: object
```

iris_frame.shape

2. To check data completeness

Here we check whether there are some NAs or Empty values

In [69]:
```
iris_frame.isnull().sum()
```

Out[69]:
```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
target          0
name            0
dtype: int64
```

In [70]:
```
iris_frame.isna().sum()
```

Out[70]:
```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
target          0
name            0
dtype: int64
```

Conclusion: data is full, no need any additional data mining

3. To check data balance

Here we check the number of examples in each class

In [72]:
```
iris_frame \
            .groupby('name') \
            .agg({'target':'count'}) \
            .rename(columns ={'target':'# of examples'})
```

Out[72]:

name	# of examples
setosa	50
versicolor	50
virginica	50

Conclusion: data is balanced well

4. To buld some visualization to understand data structure

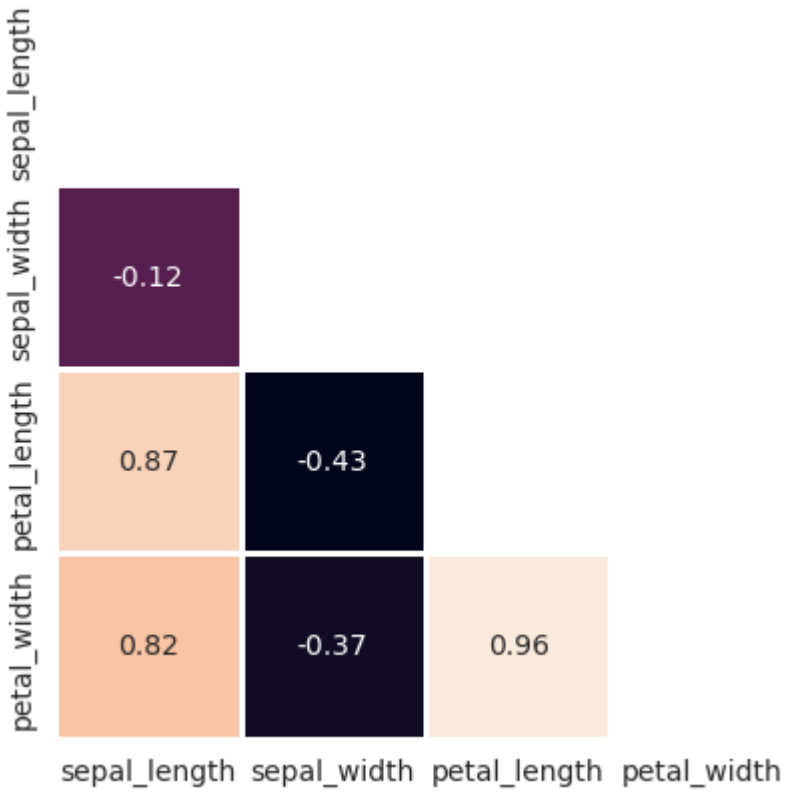
Corelation matrix shows us that the corelation between several feachers are high.

They are:

1. petal_length vs sepal_length
2. petal_with vs sepal_length
3. petal_length vs petal_with

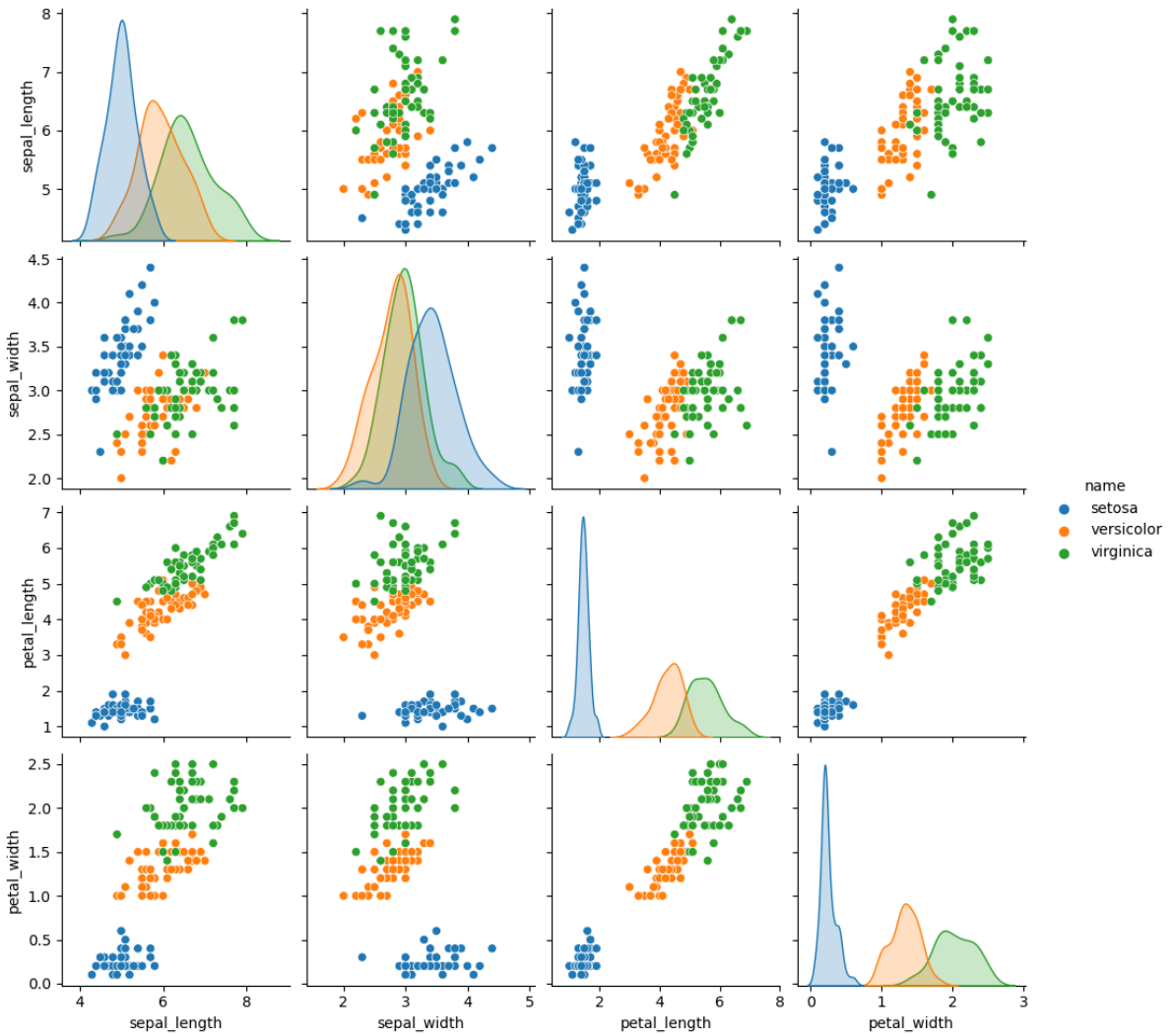
All the rest feachers have low or not significant correlation.

In [78]:
```
coef_cor = iris_frame[iris_frame.columns[0:-2]].corr()
mask = np.zeros_like(coef_cor)
mask[np.triu_indices_from(mask)] = True
with sns.axes_style("white"):
    ax = sns.heatmap(coef_cor, mask=mask, square=True, cbar=False, annot=True, line
```



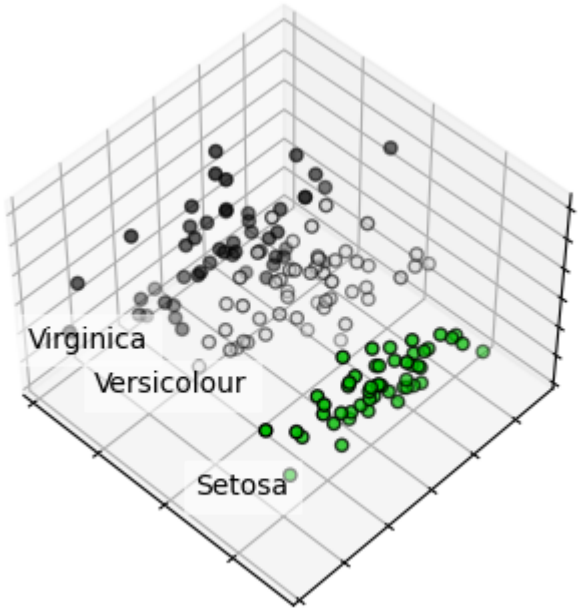
Here we build pair plot to vizualize, how features are distributed in space. It is visible that one class "setosa" is separated from the rest two.

In [54]:
```
# pairplot:
sns.pairplot(iris_frame.drop(columns = ['target']), hue='name');
```



In [63]:
```
        np.random.seed(5)
        X = iris_frame.drop(columns = ['target', 'name'])
        y = iris_frame.target

        fig = plt.figure(1, figsize=(4, 3))
        plt.clf()

        ax = fig.add_subplot(111, projection="3d", elev=48, azim=134)
        ax.set_position([0, 0, 0.95, 1])

        plt.cla()
        pca = decomposition.PCA(n_components=3)
        pca.fit(X)
        X = pca.transform(X)

        for name, label in [("Setosa", 0), ("Versicolour", 1), ("Virginica", 2)]:
```

```
            ax.text3D(
                X[y == label, 0].mean(),
                X[y == label, 1].mean() + 1.5,
                X[y == label, 2].mean(),
                name,
                horizontalalignment="center",
                bbox=dict(alpha=0.5, edgecolor="w", facecolor="w"),
            )
        # Reorder the labels to have colors matching the cluster results
        y = np.choose(y, [1, 2, 0]).astype(float)
        ax.scatter(X[:, 0], X[:, 1], X[:, 2], c=y, cmap=plt.cm.nipy_spectral, edgec

        ax.xaxis.set_ticklabels([])
        ax.yaxis.set_ticklabels([])
        ax.zaxis.set_ticklabels([])

        plt.show()
```



In [ ]:

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