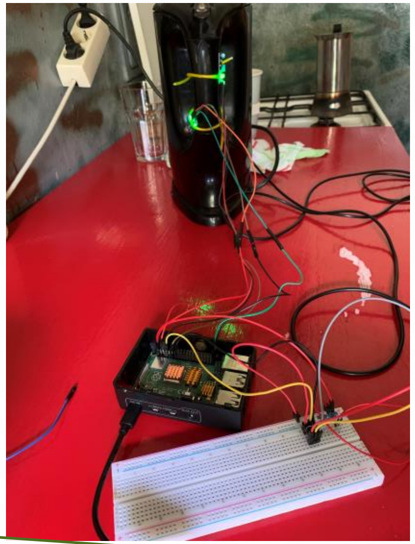
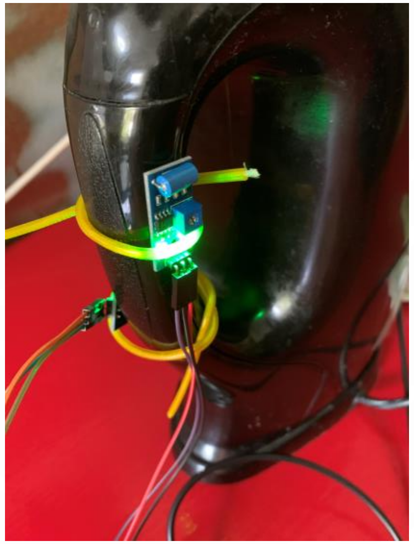
INTERNET OF THINGS AND MACHINE LEARNING USING THE EXAMPLE OF PREDICTIVE MAINTENANCE

WHAT IS THE INTERNET OF THINGS?

“The Internet of Things (IoT) refers to the connectivity of physical objects, equipped with sensors and actuators, to the Internet via data communication technology, enabling interaction with and/or among these objects.“

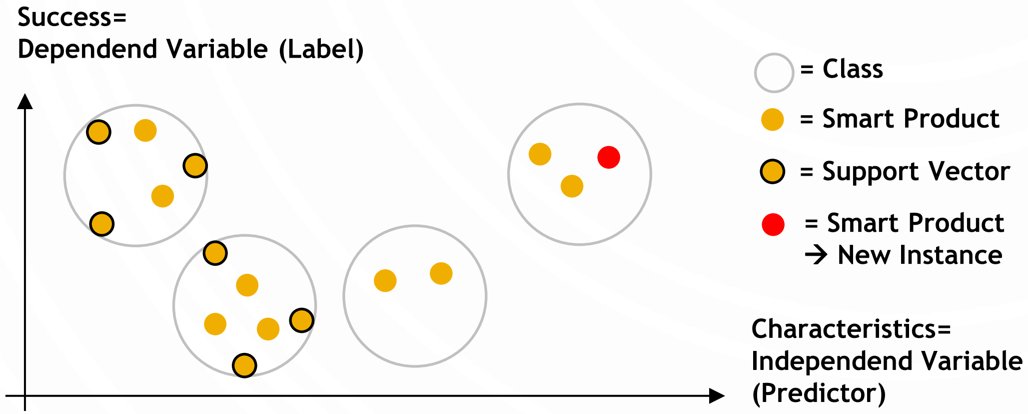
PROJECT QUESTION: IS IT POSSIBLE TO PREDICT THE FILLING LEVEL OF AN ELECTRIC KETTLE TO DETERMINE THE FILLING LEVEL?





✔ Prediction with Machine Learning Approach

PREDICTION BASED ON SUPPORT VECTOR MACHINE!



Explanation
• **SVM trains** on the basis of **characteristics** and **market success** of the smart products • **Depending** on the **characteristics** of the smart product, it will have a **certain success** • **Success** results from **Google search queries** • **Apply SVM** to an entirely **new object/instance**

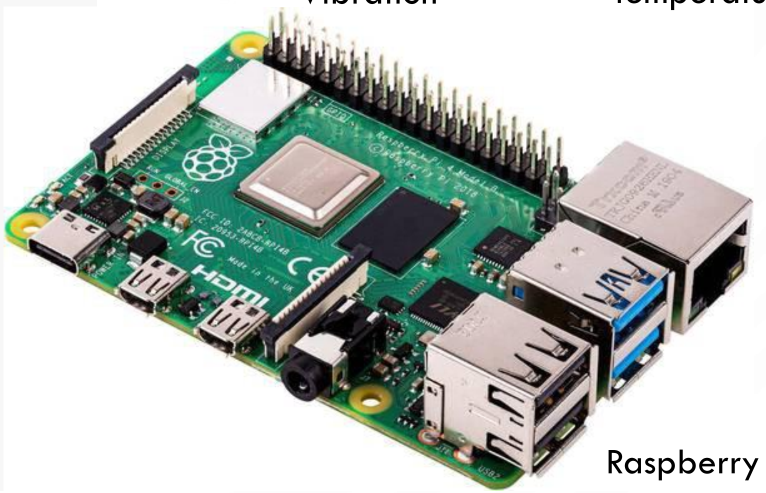
DATA GATHERING WITH RASPBERRY PI AND SENSORS

```python
# DS18B20. Reads temperature data from one wire
def read_temp_data():

    # With command ls in cd /sys/bus/w1/devices in the console the 'sensor id' can be read
    # With cat 'sensor id' the sensor data can be shown
    sensor_id = '28-0120333c7ec8'
    sensor_directory = f'/sys/bus/w1/devices/{sensor_id}/w1_slave'

    f = open(sensor_directory, 'r')
    lines = f.readlines()
    f.close()
    return lines

# SW420. Reads vibration data
def read_vibration_data():

    channel = 17
    GPIO.setmode(GPIO.BCM)
    GPIO.setup(channel, GPIO.IN)

    if GPIO.input(channel)==True:
        return 1
    else:
        return 0

# Reads data from acustic sensor
def read_acustic_data():

    channel = 21
    GPIO.setmode(GPIO.BCM)
    GPIO.setup(channel, GPIO.IN)

    if GPIO.input(channel)==True:
        return 0
    else:
        return 1
```


Sound


Vibration


Temperature


Raspberry Pi

DATA IMPORT

```
import pandas as pd
import matplotlib.pyplot as plt
# %matplotlib inline
import numpy as np
import glob

# Load data
path = r'_Sensor_Data/'
all_files = glob.glob(path + "/*.csv")

li = []

for filename in all_files:
    df = pd.read_csv(filename, index_col=None, header=None)
    li.append(df)
```

- Gathering data for filling levels 0.5, 1.0 and 1.5 litre
- In sum about 6700 landmarks
  (i.e. about 220 landmarks per measurement)

Time Stamp	Temperature Raw	Temperature	Vibration	Acustic
2020-09-16 15:18:14.564406	92437	92.437	0	0
2020-09-16 15:18:15.524435	92375	92.375	0	0
2020-09-16 15:18:16.484355	92312	92.312	0	1
…	…	…	…	…

Excluding vibration sensor, since the sensor was not sensitive enough

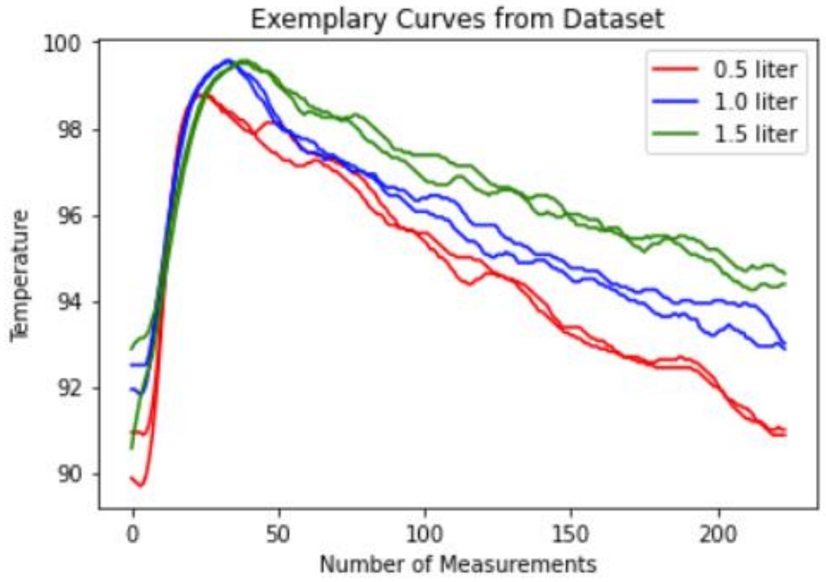
DATA PREPARATION AND LABELING

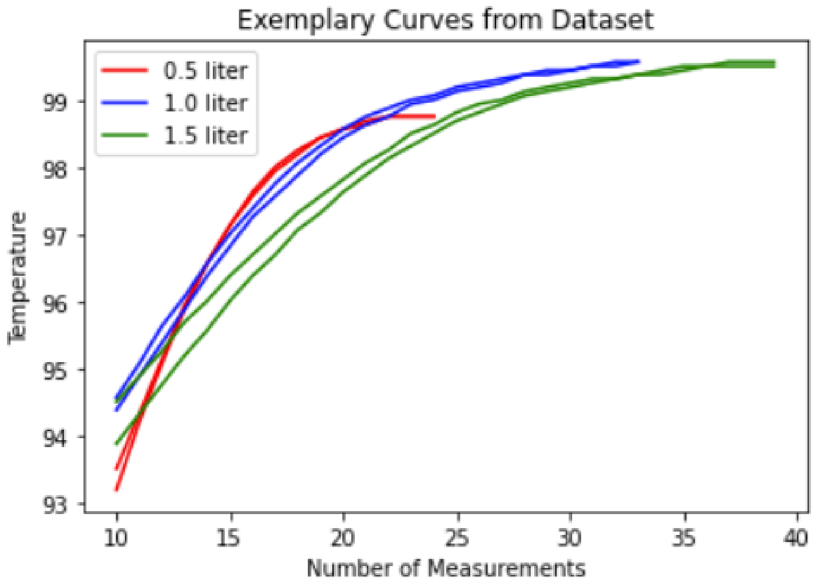
```
# Seperate data based on liter
data_half_liter = li[0:12]
data_one_half_liter = li[12:23]
data_one_liter = li[23:]

# Seperate data based on liter and measurement as numpy arrays
data_half_liter_1 = np.array(data_half_liter[0])
data_half_liter_2 = np.array(data_half_liter[1])
data_half_liter_3 = np.array(data_half_liter[2])
data_half_liter_4 = np.array(data_half_liter[3])
data_half_liter_5 = np.array(data_half_liter[4])
data_half_liter_6 = np.array(data_half_liter[5])
data_half_liter_7 = np.array(data_half_liter[6])
data_half_liter_8 = np.array(data_half_liter[7])
data_half_liter_9 = np.array(data_half_liter[8])
data_half_liter_10 = np.array(data_half_liter[9])
```

	Temperature	Sound	Filling Level
0	1260.872	1.0	500.0
1	1260.058	0.0	500.0
2	1213.621	1.0	500.0
3	1262.058	2.0	500.0
4	1256.934	2.0	500.0
5	1268.810	0.0	500.0
6	1260.934	0.0	500.0
7	1233.560	1.0	500.0
8	1259.746	0.0	500.0
9	1259.872	0.0	500.0
10	2741.619	8.0	1000.0
11	2753.055	2.0	1000.0
12	2750.432	5.0	1000.0
13	2694.432	5.0	1000.0
14	2752.806	5.0	1000.0

DATA VISUALIZATION

```python
# Plot exemplary data from pandas data frames

x_axis_seconds = np.arange(0,224,1)

data_half_liter_1_df = pd.DataFrame(data_half_liter_1)
data_half_liter_2_df = pd.DataFrame(data_half_liter_2)

data_one_liter_1_df = pd.DataFrame(data_one_liter_3)
data_one_liter_2_df = pd.DataFrame(data_one_liter_2)

data_one_half_liter_1_df = pd.DataFrame(data_one_half_liter_3)
data_one_half_liter_2_df = pd.DataFrame(data_one_half_liter_2)

plt.plot(x_axis_seconds, data_half_liter_1_df[2], c="red", label="0.5 liter")
plt.plot(x_axis_seconds, data_half_liter_2_df[2], c="red")

plt.plot(x_axis_seconds, data_one_liter_1_df[2], c="blue", label="1.0 liter")
plt.plot(x_axis_seconds, data_one_liter_2_df[2], c="blue")

plt.plot(x_axis_seconds, data_one_half_liter_1_df[2], c="green", label="1.5 liter")
plt.plot(x_axis_seconds, data_one_half_liter_2_df[2], c="green")
plt.xlabel("Number of Measurements")                # label of the y axis
plt.ylabel("Temperature")                           # label of the y axis
plt.title("Exemplary Curves from Dataset")
plt.legend()
```





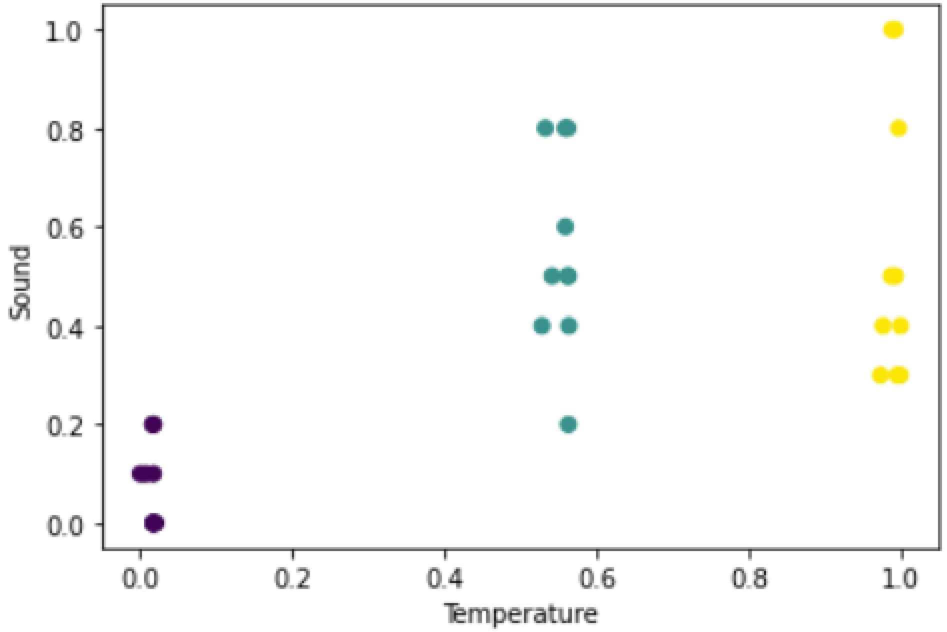
STANDARDIZATION OF DATA

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
scaler.fit(data_aggr)
data_aggr_scaled = scaler.transform(data_aggr)
len(data_aggr_scaled[:,0])
data_aggr_scaled
```

```
array([[0.01728515, 0.1       , 0.        ],
       [0.01698738, 0.        , 0.        ],
       [0.        , 0.1       , 0.        ],
       [0.01771901, 0.2       , 0.        ],
       [0.01584457, 0.2       , 0.        ],
       [0.02018899, 0.        , 0.        ],
       [0.01730783, 0.        , 0.        ],
       [0.007294  , 0.1       , 0.        ],
       [0.01687324, 0.        , 0.        ],
       [0.01691934, 0.        , 0.        ],
       [0.55896544, 0.8       , 0.5       ],
```

```
plt.scatter(data_aggr_scaled[:,0], data_aggr_scaled[:,1], c=data_aggr_scaled[:,2])
plt.xlabel("Temperature")
plt.ylabel("Sound")
plt.show()
```

Visualiziation Combination Sound and Temperature



SELECT, APPLY AND FINE-TUNE MODEL (POLY)

```
from sklearn.svm import SVC # Support Vector Machine Approach
from sklearn.multiclass import OneVsRestClassifier # Approach for multiple classes
from sklearn.model_selection import GridSearchCV # Grid Search to find best parameter combination
from sklearn.preprocessing import label_binarize # Convert textual classes in binary classes
from sklearn.model_selection import train_test_split # Split data set into a train and test set
from sklearn.model_selection import cross_val_score # For explanation please show internet
from sklearn.metrics import mean_squared_error # For calculating lost function

svm_grid_search = OneVsRestClassifier(SVC())

parameters = {
          "estimator__kernel": ["poly"],
          "estimator__C": [4,5,6,7,8,10,12,14,16,18,20,22,24,26,28,30,32],
          "estimator__degree": [1, 2, 3, 4, 5],
          "estimator__gamma": [1,2, 3, 4,5],
          "estimator__coef0": [0,1,2,3]
          }

grid_search = GridSearchCV(svm_grid_search, parameters, cv=8, scoring="accuracy", return_train_score=True)
grid_search.fit(data_aggr_scaled[:,0:2], filling_level_shaped)

print(grid_search.best_params_)
print(grid_search.best_score_)
```

```
{'estimator__C': 4, 'estimator__coef0': 1, 'estimator__degree': 2, 'estimator__gamma': 1, 'estimator__kernel': 'poly'}
1.0
```

SELECT, APPLY AND FINE-TUNE MODEL (RBF)

```
svm_grid_search = OneVsRestClassifier(SVC())
parameters = {
          "estimator__kernel": ["rbf"],
          "estimator__C": [1,2,4,6,8,10,12,14, 50, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000],
          "estimator__gamma": [10,15,20,25,30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100]
          }

grid_search = GridSearchCV(svm_grid_search, parameters, cv=8, scoring="accuracy", return_train_score=True)
grid_search.fit(data_aggr_scaled[:,0:2], filling_level_shaped)

print(grid_search.best_params_)
print(grid_search.best_score_)
```

```
{'estimator__C': 1, 'estimator__gamma': 10, 'estimator__kernel': 'rbf'}
1.0
```

PREDICTION WITH THE MODEL (POLY)

```
# Predict the fill level Poly
fill_level_poly = OneVsRestClassifier(SVC(kernel="poly",C=4, degree=2, gamma=1, coef0=1))
fill_level_poly.fit(X_train, y_train)
```

```
OneVsRestClassifier(estimator=SVC(C=4, coef0=1, gamma=4, kernel='poly'))
```

```
fill_level_poly.predict(X_test[0,:].reshape(1, -1))
```

```
array([500.])
```

```
y_test
```

```
array([[ 500.],
       [1500.],
       [1000.],
       [1000.],
       [1500.],
       [1500.],
       [1500.],
       [1000.]])
```

PREDICTION WITH THE MODEL (RBF)

```
# Predict the fill level RBF
fill_level_rbf = OneVsRestClassifier(SVC(kernel="rbf",C=1, gamma=10))
fill_level_rbf.fit(X_train, y_train)
```

```
fill_level_poly.predict(X_test[0,:].reshape(1, -1))
```

```
array([500.])
```

```
y_test
```

```
array([[ 500.],
       [1500.],
       [1000.],
       [1000.],
       [1500.],
       [1500.],
       [1500.],
       [1000.]])
```

CONCLUSION

Learnings

- High effort in data acquisition using Raspberry Pis and associated sensor technology
- Simple approaches are sometimes more effective
- Some sensors do not contribute to the explanation of the model, since they are unsuitable

- End-to-end data analytics or machine learning project was implemented
    - From big picture to data collection and evaluation to presentation
    - Especially how to collect data with hardware and sensors
    - Challenge solved: Unstructured initial real world use case