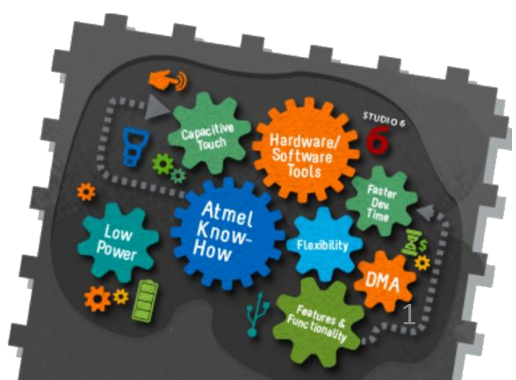
tiny Machine Learning



Intelligent edge devices with rich sensors (e.g., billions of mobile phones and IoT devices) have been ubiquitous in our lives.

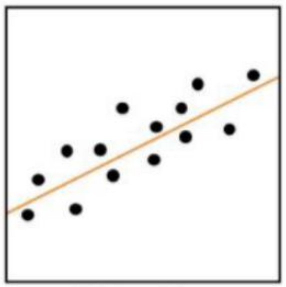
Deploying artificial intelligence (AI) to these edge devices is attractive for many real-world applications: smart home, smart retail, smart manufacturing, autonomous driving, and more.

However, state-of-the-art deep learning systems typically require tremendous amount of resources (e.g., memory, computation, data, AI experts), both for training and inference.

This hinders the application powerful deep learning systems on edge devices.

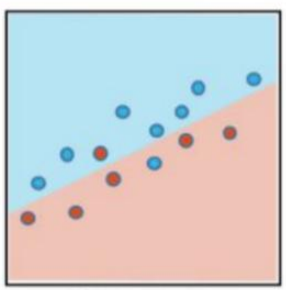
TinyML project aims to improve the efficiency of deep learning by requiring ***less computation***, ***fewer engineers***, and ***less data***, from algorithm to hardware, from inference to training. <u>Embrace the era of edge AI and AIoT</u>.

Common Challenges



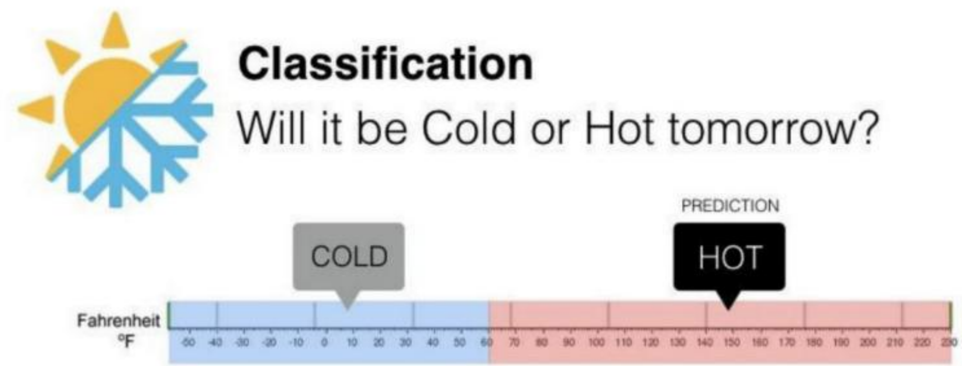
a) Regression

Regression



b) Classification

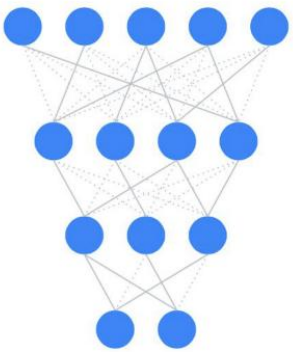
Classification



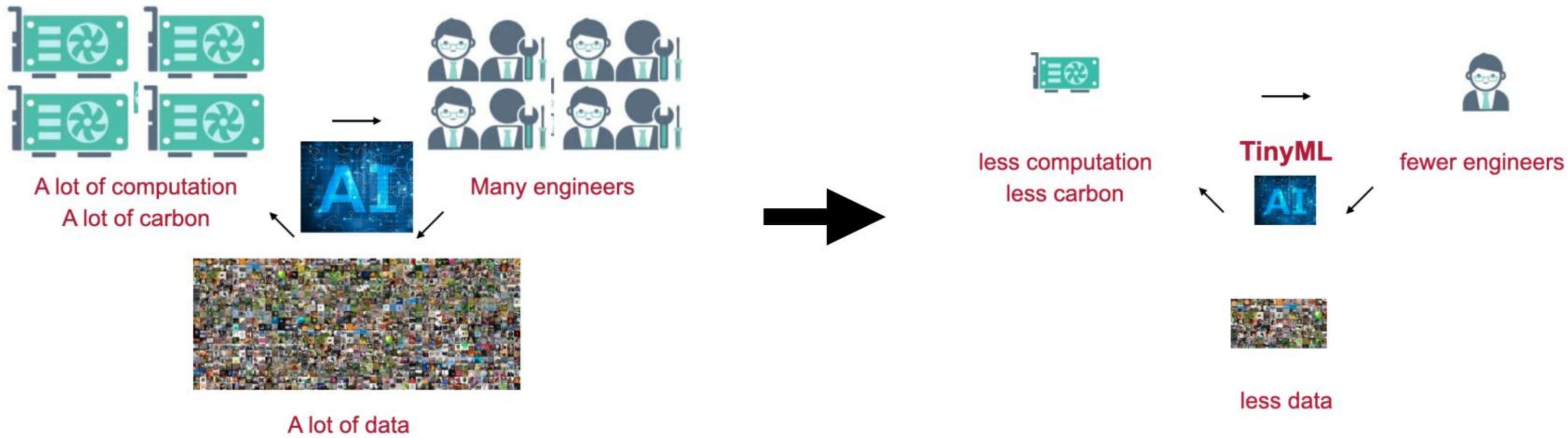
tiny Machine Learning

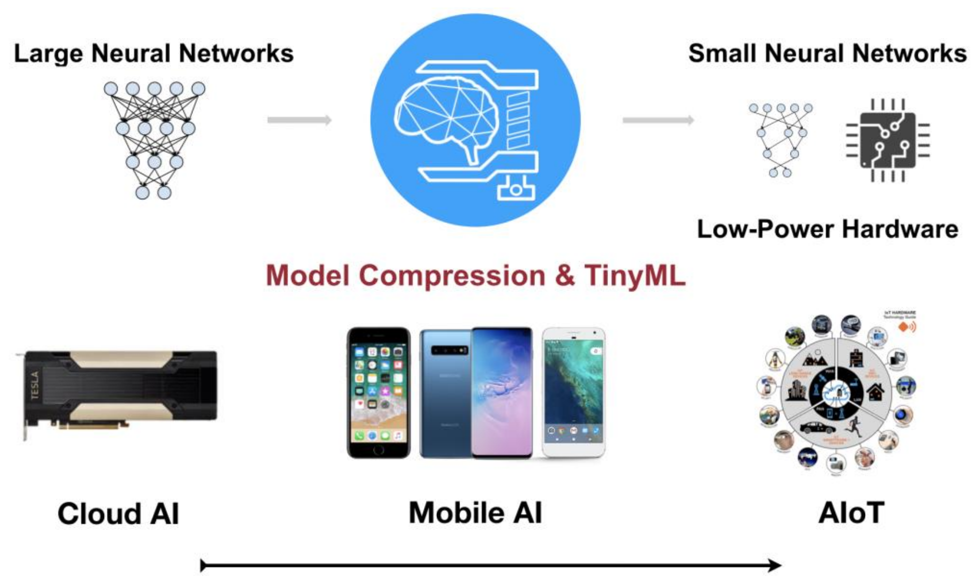
Machine Learning vs Deep Learning

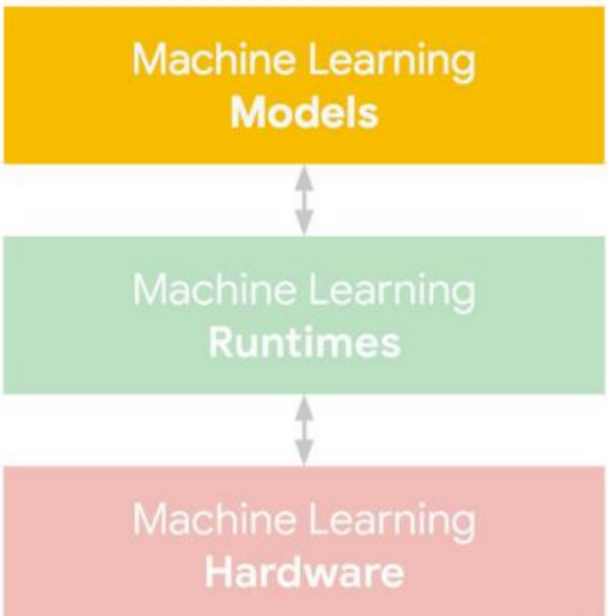
- DecisionTree
- RandomForest
- XGBoost
- GaussianNB
- Support Vector Machines (SVC and OneClassSVM)
- Relevant Vector Machines (from skbayes.rvm_ard_models package)
- SEFR
- PCA



- CNN
- DNN
- RNN
- AutoEncoder
- GAN
- Transformers


A lot of computation
A lot of carbon
Many engineers
AI
A lot of data
less computation
less carbon
TinyML
AI
fewer engineers
less data


Large Neural Networks
Small Neural Networks
Low-Power Hardware
Model Compression & TinyML
Cloud AI
Mobile AI
AIoT



Model Compression Techniques

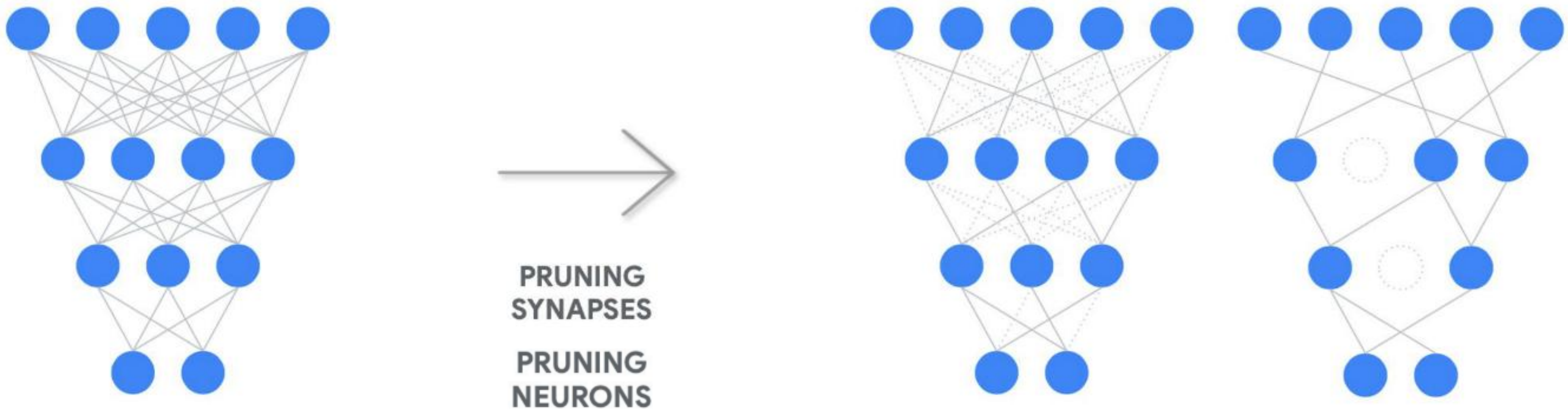
Pruning

Quantization

Knowledge Distillation

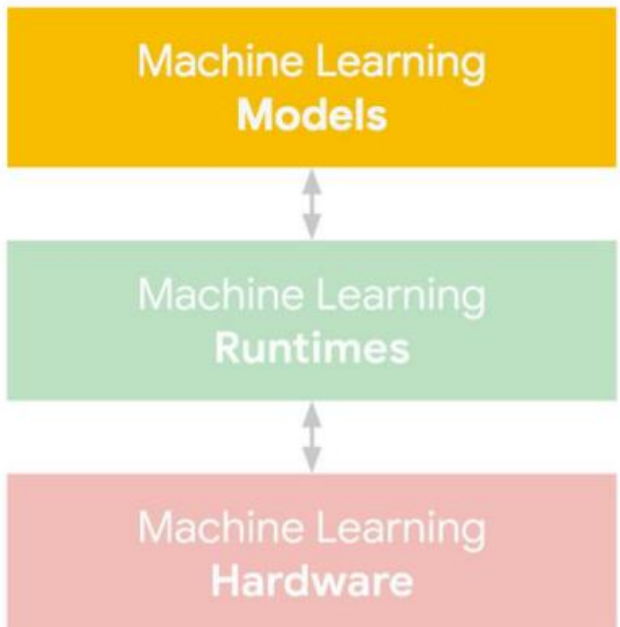
...

Pruning



Weight pruning means eliminating unnecessary values in the weight tensors. Practically setting the neural network parameters' values to zero to remove what we estimate are unnecessary connections between the layers of a neural network.

This is done during the training process to allow the neural network to adapt to the changes.



Model Compression Techniques

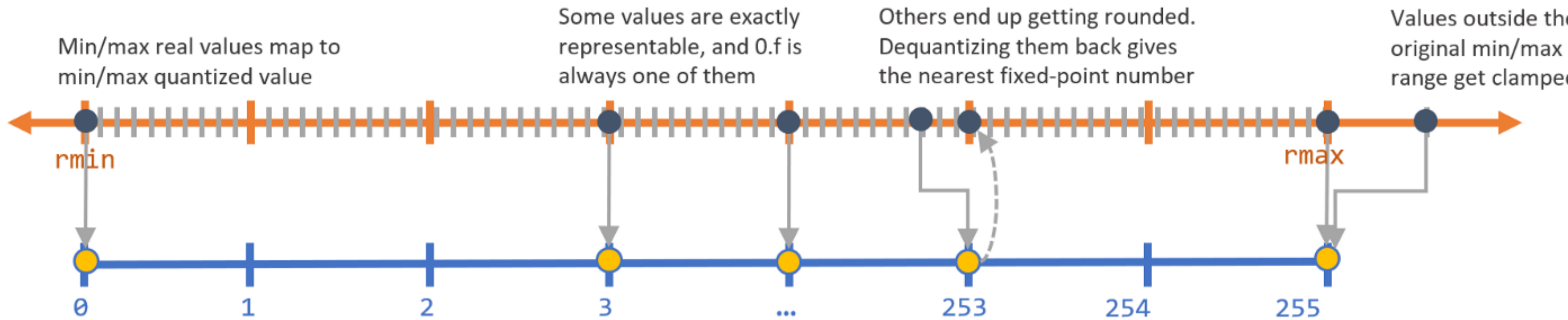
Pruning

Quantization

Knowledge Distillation

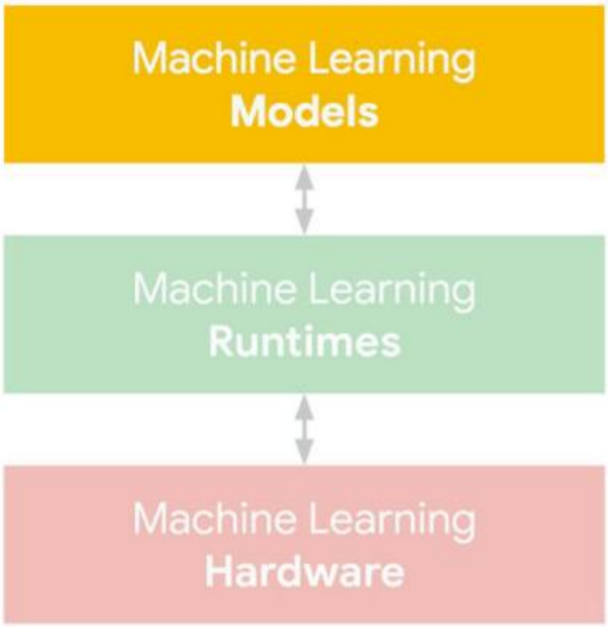
...

Quantization



Quantization is the process of transforming an ML model into an equivalent representation that uses parameters and computations at a lower precision. This improves the model's execution performance and efficiency. For example, TensorFlow Lite 8-bit integer quantization results in models that are up to 4x smaller in size, 1.5x-4x faster in computations, and lower power consumption on CPUs.

However, the process of going from higher to lower precision is lossy in nature. As seen in the image below, quantization squeezes a small range of floating-point values into a fixed number of information buckets.



Model Compression Techniques

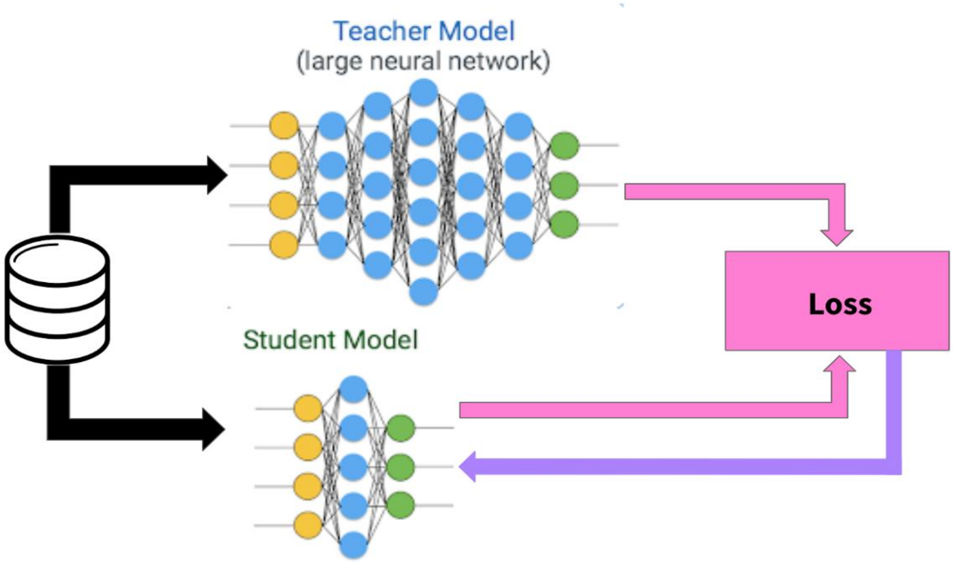
Pruning

Quantization

Knowledge Distillation

...

Knowledge distillation

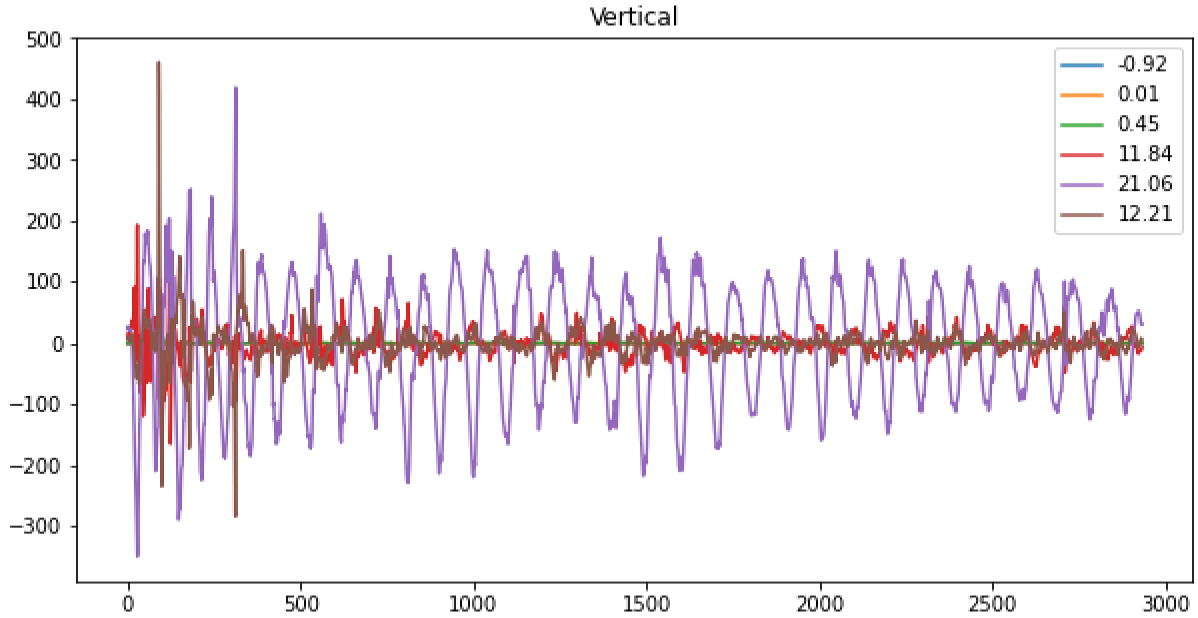


Knowledge Distillation is a procedure for model compression, in which a small (student) model is trained to match a large pre-trained (teacher) model. Knowledge is transferred from the teacher model to the student by minimizing a loss function, aimed at matching softened teacher logits as well as ground-truth labels.

Learn by doing…

Machine Learning version vs Deep Learning Model

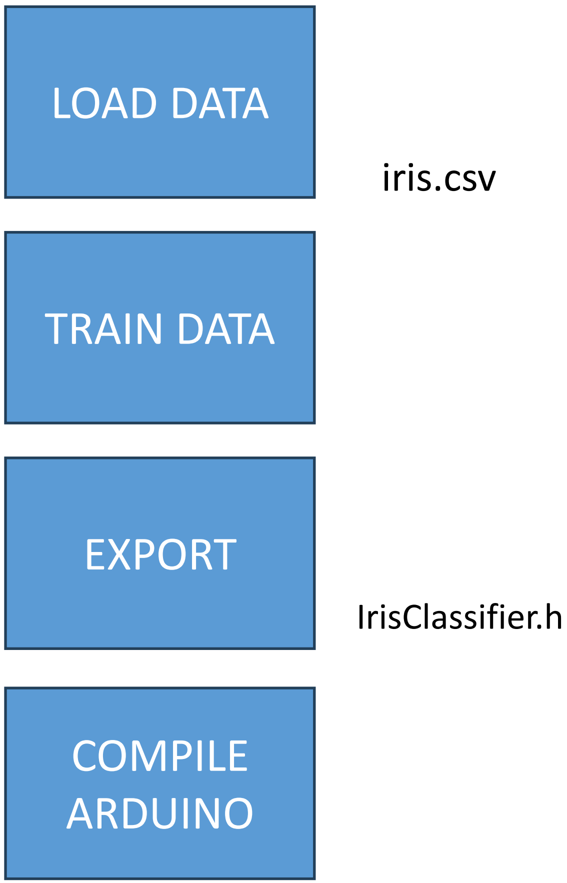
Gesture Recognition: the Machine Learning way



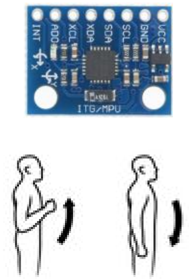
DEMO

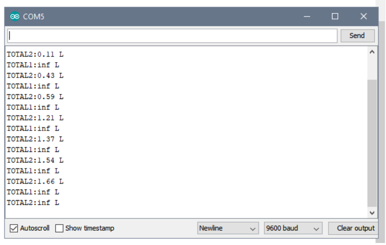
pip install everywhereml

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from everywhereml.sklearn.ensemble import RandomForestClassifier


def load_data_from_csv(filename: str, label_column: str) -> tuple:
    """
    Convert csv file to X and y
    :param label_column:
    :param filename:
    :return:
    """
    df = pd.read_csv(filename)
    x_columns = [c for c in df.columns if c != label_column]
    X = df[x_columns].to_numpy(dtype=float)
    y_string = df[label_column]
    label_encoder = LabelEncoder().fit(y_string)
    y_numeric = label_encoder.transform(y_string)
    print('Label mapping', {label: i for i, label in enumerate(label_encoder.classes_)})

    return X, y_numeric


X, y = load_data_from_csv('iris.csv', label_column='variety')
clf = RandomForestClassifier(n_estimators=5).fit(X, y)

import sys
sys.stdout = open('IrisClassifier.h','wt')
print(clf.to_arduino(instance_name='irisClassifier'))
```



Exercise: Capture and train data





Step 1.1 Record the "no gesture" gesture

Record.ino

- Arm at rest position
- Move slowly to add some noise
- min. of 20 secs
- save data from terminal to file “rest.csv”

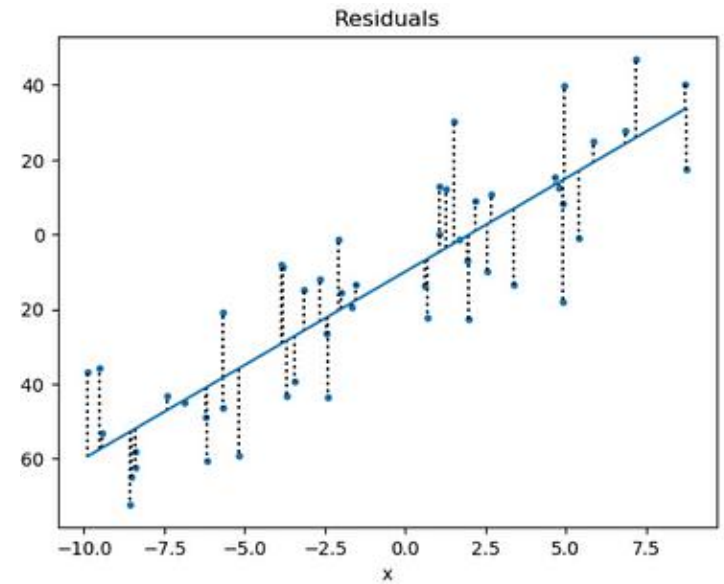
Step 1.2 Record all the other gestures

- 4 different movements (Left, Right, Front, Up)
- min. of 20 secs for each motion/repetition
- save data from terminal to file “xxx.csv”

tiny Machine Learning

Linear Regression

…is a statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. It is one of the simplest and most used techniques in statistical modelling and machine learning for predictive analysis.



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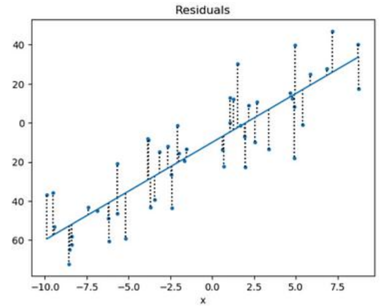

Linear Regression

…relies on several key assumptions to provide reliable and valid results.

A. **Linearity:** The relationship between dependent and independent variables should follow a straight-line pattern, meaning changes in the independent variables proportionally affect the dependent variable.

B. **Independence of Errors:** Residuals should not be correlated with each other; each observation's error should be independent. Autocorrelation may indicate missing variables or model issues.

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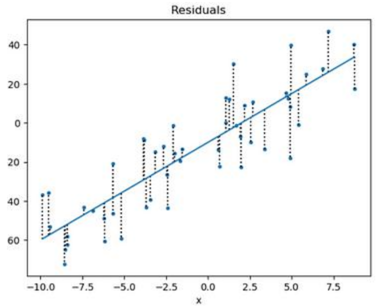

Linear Regression

C. **Homoscedasticity:** The variance of errors should remain constant across all values of the independent variables. Inconsistent variance (heteroscedasticity) can lead to biased estimates.

D. **Normality of Errors:** Residuals should follow a normal distribution to ensure accurate statistical inference, hypothesis testing, and confidence intervals.

E. **No Perfect Multicollinearity:** Independent variables should not be perfectly correlated, as this makes coefficient estimation unstable and unreliable.

F. **Zero Conditional Mean:** The average error should be zero across all values of independent variables, ensuring unbiased predictions without systematic over- or underestimation.

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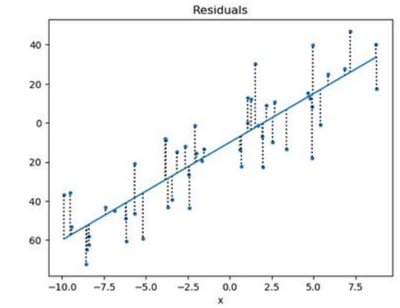

Linear Regression - Model

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

- *Y* is the dependent variable.
- *X* is the independent variable.
- *β*0 is the intercept (the value of *Y* when *X*=0).
- *β*1 is the slope (the change in *Y* for a one-unit change in *X*).
- *ε* represents the error term, which captures the difference between the observed and predicted values.

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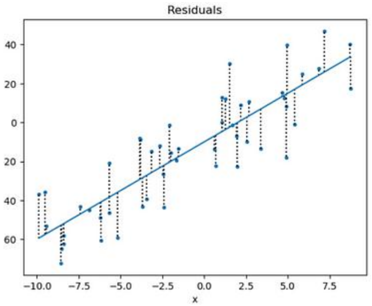
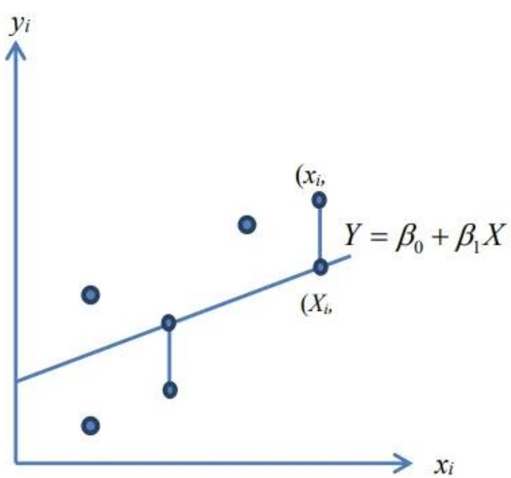


Linear Regression - Coefficients

The coefficients $\beta 0, \beta 1, \ldots, \beta n$ are estimated using the method of least squares. This method minimizes the sum of the squared differences between the observed values of the dependent variable and the values predicted by the linear model.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$



- *yi* is the observed value of the dependent variable for the *i*th observation.
- *y^i* is the predicted value of the dependent variable for the *i*th observation based on the linear regression model.
- *n* is the number of observations.

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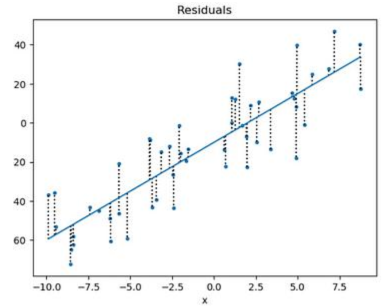
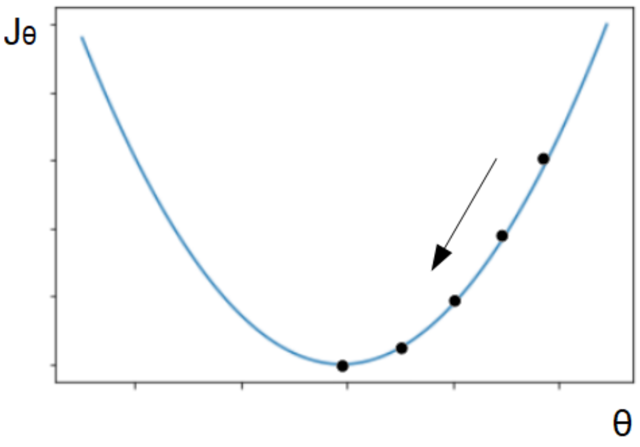


Linear Regression –

Minimizing the Objective Function

Gradient descent is an iterative optimization algorithm used to minimize the MSE by adjusting the coefficients in the direction of the negative gradient of the MSE with respect to each coefficient.



$$\beta_j^{(t+1)} = \beta_j^{(t)} - \alpha \frac{\partial}{\partial \beta_j} \mathrm{MSE}$$

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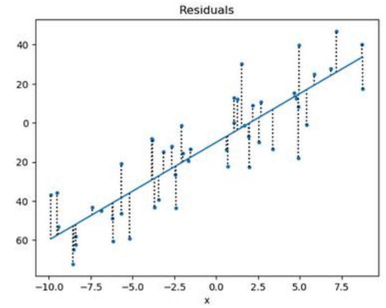
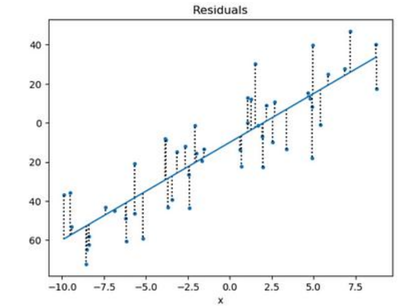


Linear Regression -

In practice (step by step)

Importing libraries
Load Dataset
Exploratory Data Analysis
Splitting the data
Feature selection
Training the model
Evaluating the model
Export Model
Run in Arduino



tiny Machine Learning

Linear Regression -

In practice (step by step)

```
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.calibration import LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from micromlgen import port
import pylab
import scipy.stats as stats
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

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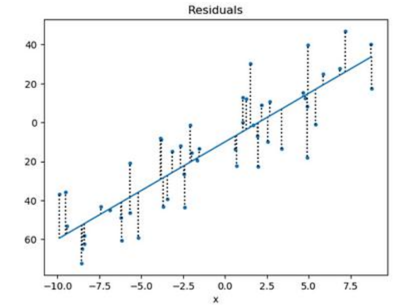
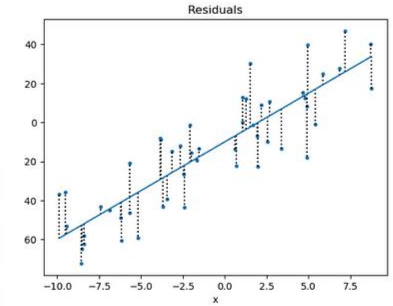



```
# Load dataset
data = load_diabetes() # load data

# Create a DataFrame
df_diabetes = pd.DataFrame(data.data, columns=data.feature_names)


# Add target variable to the DataFrame
df_diabetes['target'] = data.target

# Remove NaN values
df = df_diabetes.dropna(axis='rows') #remove NaN

# Display the DataFrame
df_diabetes.head()
df_diabetes.info()
df_diabetes.describe()
```

tiny Machine Learning

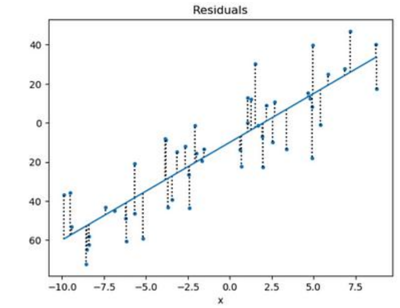


	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	442.000000
mean	-2.511817e-19	1.230790e-17	-2.245564e-16	-4.797570e-17	-1.381499e-17	3.918434e-17	-5.777179e-18	-9.042540e-18	9.293722e-17	1.130318e-17	152.133484
std	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	77.093005
min	-1.072256e-01	-4.464164e-02	-9.027530e-02	-1.123988e-01	-1.267807e-01	-1.156131e-01	-1.023071e-01	-7.639450e-02	-1.260971e-01	-1.377672e-01	25.000000
25%	-3.729927e-02	-4.464164e-02	-3.422907e-02	-3.665608e-02	-3.424784e-02	-3.035840e-02	-3.511716e-02	-3.949338e-02	-3.324559e-02	-3.317903e-02	87.000000
50%	5.383060e-03	-4.464164e-02	-7.283766e-03	-5.670422e-03	-4.320866e-03	-3.819065e-03	-6.584468e-03	-2.592262e-03	-1.947171e-03	-1.077698e-03	140.500000
75%	3.807591e-02	5.068012e-02	3.124802e-02	3.564379e-02	2.835801e-02	2.984439e-02	2.931150e-02	3.430886e-02	3.243232e-02	2.791705e-02	211.500000
max	1.107267e-01	5.068012e-02	1.705552e-01	1.320436e-01	1.539137e-01	1.987880e-01	1.811791e-01	1.852344e-01	1.335973e-01	1.356118e-01	346.000000

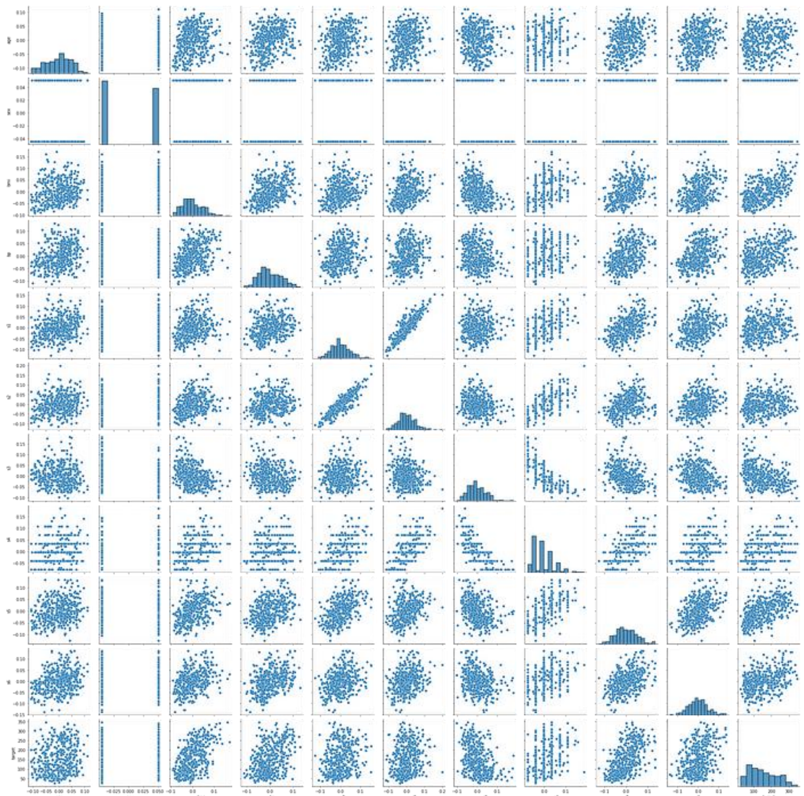
	age	sex	bmi	bp	s1	s2	s3	s4	s5	s6	target
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.019907	-0.017646	151.0
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.068332	-0.092204	75.0
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.002861	-0.025930	141.0
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.022688	-0.009362	206.0
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.031988	-0.046641	135.0

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 442 entries, 0 to 441
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   age     442 non-null    float64
 1   sex     442 non-null    float64
 2   bmi     442 non-null    float64
 3   bp      442 non-null    float64
 4   s1      442 non-null    float64
 5   s2      442 non-null    float64
 6   s3      442 non-null    float64
 7   s4      442 non-null    float64
 8   s5      442 non-null    float64
 9   s6      442 non-null    float64
 10  target  442 non-null    float64
dtypes: float64(11)
memory usage: 38.1 KB
```

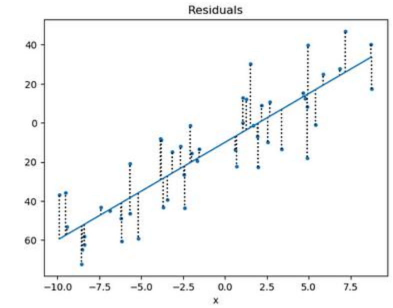
tiny Machine Learning




```
# Seaborn analysis
sns.pairplot(df_diabetes)
```

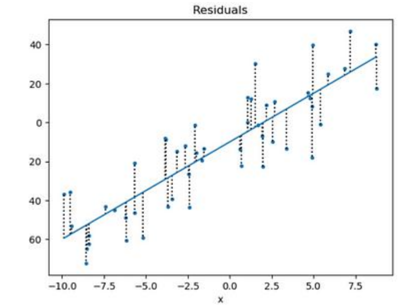


tiny Machine Learning




```
df = df_diabetes.iloc[:100,0:10]

X=df.to_numpy()

# Converting string value to int type for labels: Setosa = 0, Versicolor = 1
y=df_diabetes.iloc[:100,-1]
y = LabelEncoder().fit_transform(y)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
```

tiny Machine Learning

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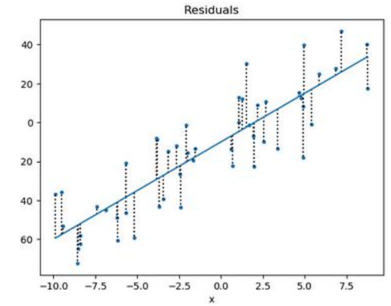
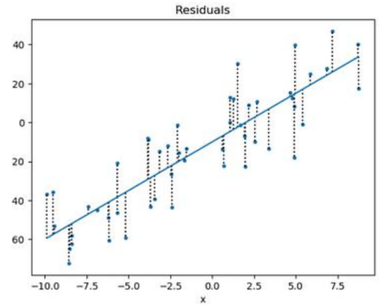
tiny Machine Learning

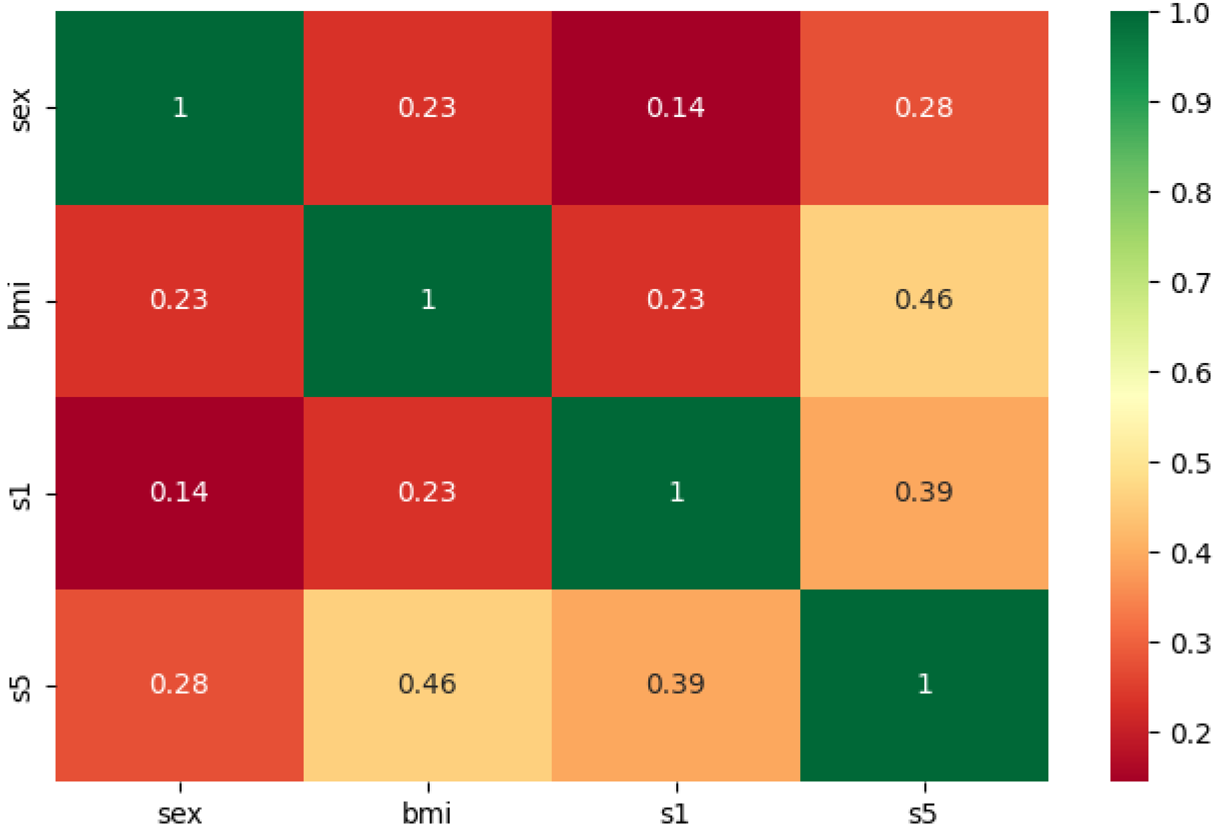


Recursive Feature Elimination (RFE)

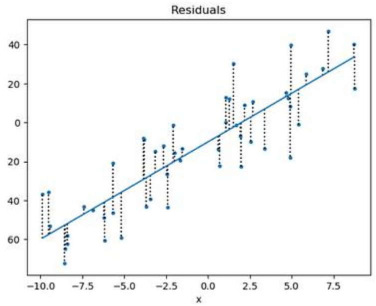
```
# Build a logreg and compute the feature importances
linearRegressor = LinearRegression()

# create the RFE model and select 5 attributes
rfe = RFE(estimator=linearRegressor, n_features_to_select=5, step=30)
rfe = rfe.fit(X_train, y_train)

# summarize the selection of the attributes
print('Selected features: %s' % list(df.columns[rfe.support_]))

selected_features = ['sex', 'bmi', 's1', 's5']
df_selected = df[selected_features]

plt.subplots(figsize=(8, 5))
sns.heatmap(df_selected.corr(), annot=True, cmap="RdYlGn")
plt.show()
```

tiny Machine Learning





tiny Machine Learning

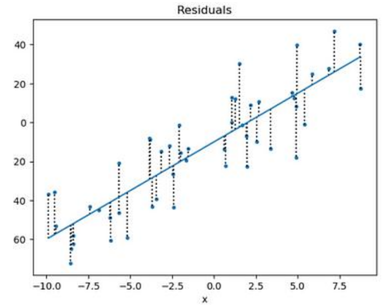


Ordinary Least Squares (OLS)

… regression analysis is a statistical method used to estimate the relationship between one or more independent variables (predictors) and a dependent variable (response).

```
# Fit the resgression line using 'OLS'
lr = sm.OLS(y_train, X_train).fit()

# Add a constant to get an intercept
X_train_sm = sm.add_constant(X_train)

# Fit the resgression line using 'OLS'
lr = sm.OLS(y_train, X_train_sm).fit()

# Print the parameters, i.e. the intercept and the slope of the regression line fitted
parameters = lr.params
print('Model fit parameter: ', parameters)

# Performing a summary operation lists out all the different parameters
print(lr.summary())
```

tiny Machine Learning



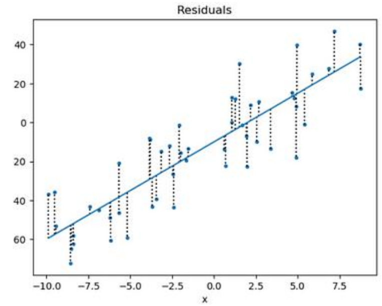
Ordinary Least Squares (OLS)

… regression analysis is a statistical method used to estimate the relationship between one or more independent variables (predictors) and a dependent variable (response).

```
predict =   parameters[0] +
            parameters[0]*X_train[:,0]+
            parameters[1]*X_train[:,1]+
            parameters[2]*X_train[:,2]+
            parameters[3]*X_train[:,3]+
            parameters[4]*X_train[:,4]+
            parameters[5]*X_train[:,5]+
            parameters[6]*X_train[:,6]+
            parameters[7]*X_train[:,7]+
            parameters[8]*X_train[:,8]+
            parameters[9]*X_train[:,9]
```

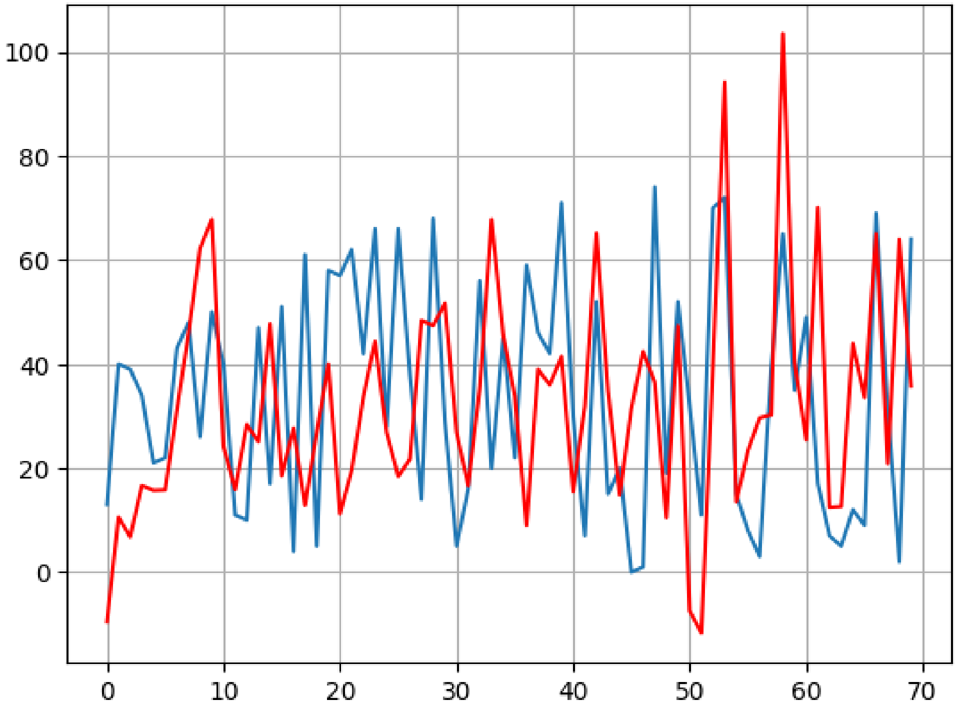
```
plt.plot(y_train)
plt.plot(predict, 'r')
plt.grid()
plt.show()
```

tiny Machine Learning

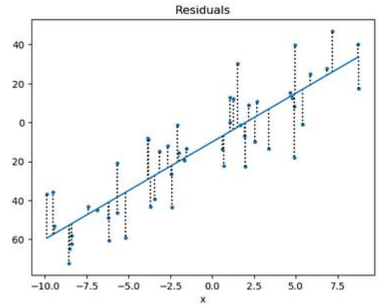


Ordinary Least Squares (OLS)

… regression analysis is a statistical method used to estimate the relationship between one or more independent variables (predictors) and a dependent variable (response).



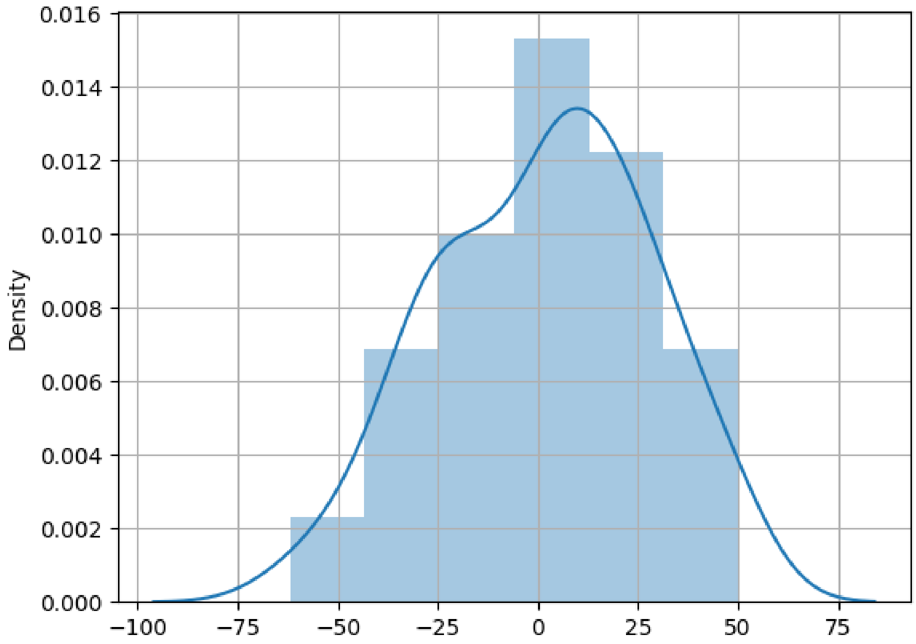
tiny Machine Learning



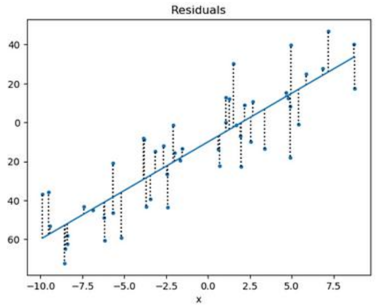
Ordinary Least Squares (OLS)

… regression analysis is a statistical method used to estimate the relationship between one or more independent variables (predictors) and a dependent variable (response).

```
residuals = y_train-predict
sns.distplot(residuals)
plt.grid()
```



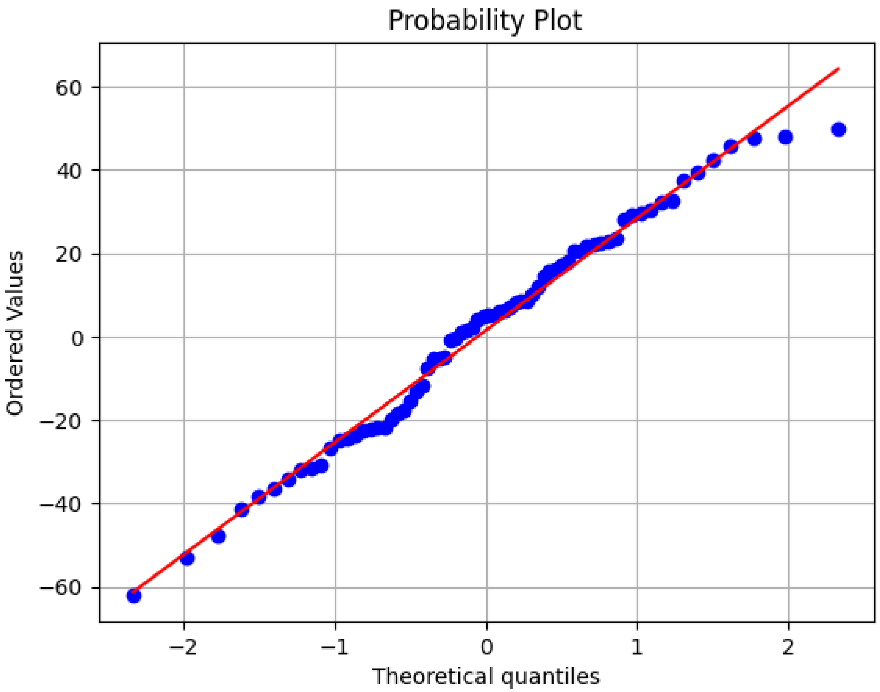
tiny Machine Learning



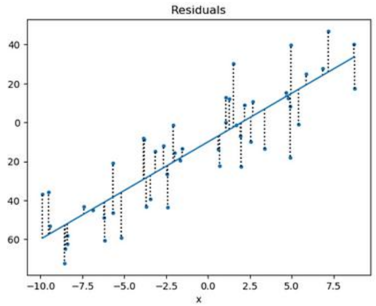
Ordinary Least Squares (OLS)

… regression analysis is a statistical method used to estimate the relationship between one or more independent variables (predictors) and a dependent variable (response).

```
stats.probplot(residuals, dist="norm", plot=pylab)
plt.grid()
pylab.show()
```

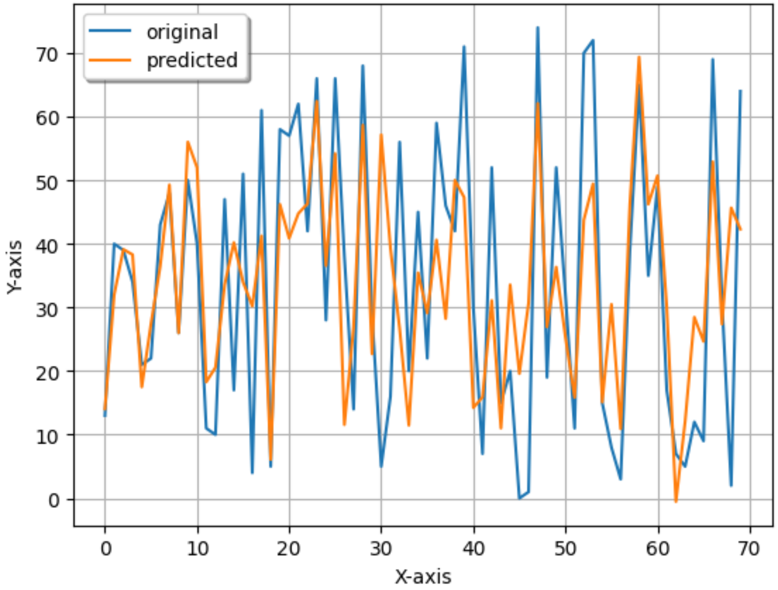


tiny Machine Learning

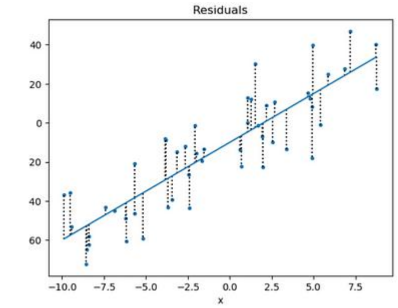


Model Evaluation

```
model = linearRegressor.fit(X_train,y_train)

predict = model.predict(X_train)

x_ax = range(len(y_train))
plt.plot(x_ax, y_train, label="original")
plt.plot(x_ax, predict, label="predicted")
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.legend(loc='best',fancybox=True, shadow=True)
plt.grid(True)
plt.show()
```



tiny Machine Learning

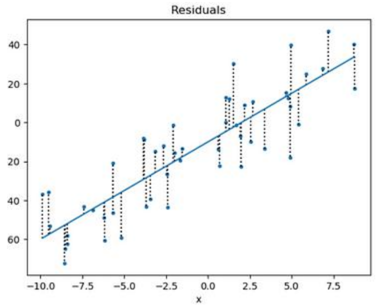


Model Evaluation

```python
score = model.score(X_train, y_train)
training_predict = model.predict(X_train)
mse = mean_squared_error(y_train, training_predict)

print("R-squared:", score)
print("MSE: ", mse)
print("RMSE: ", mse*(1/2.0))
```

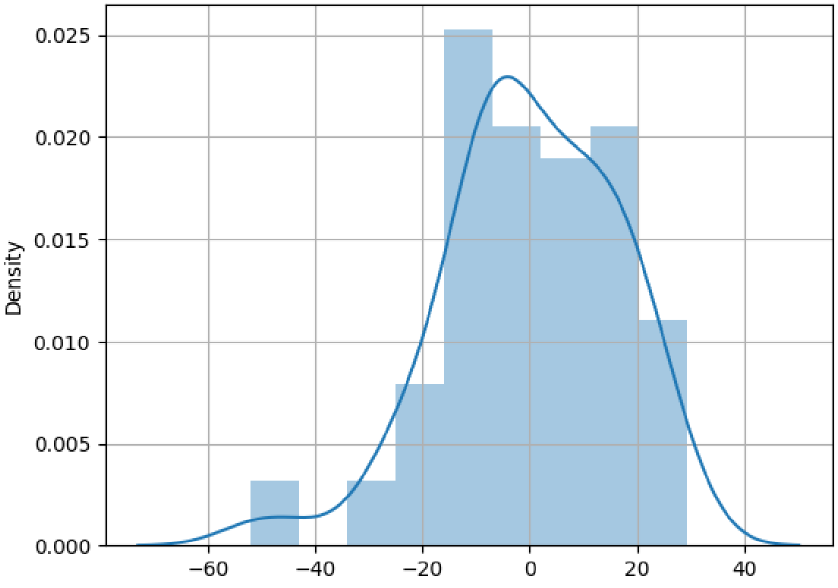
```
R-squared: 0.4665605455873243
MSE:  261.72727823900914
RMSE:  130.86363911950457
```

tiny Machine Learning

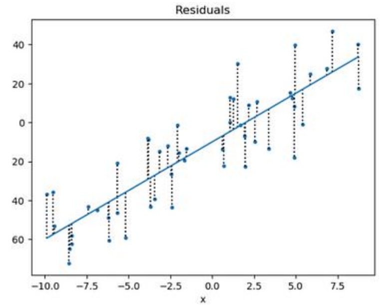


Residuals

```
residuals = y_train-training_predict
sns.distplot(residuals)
plt.grid()
```

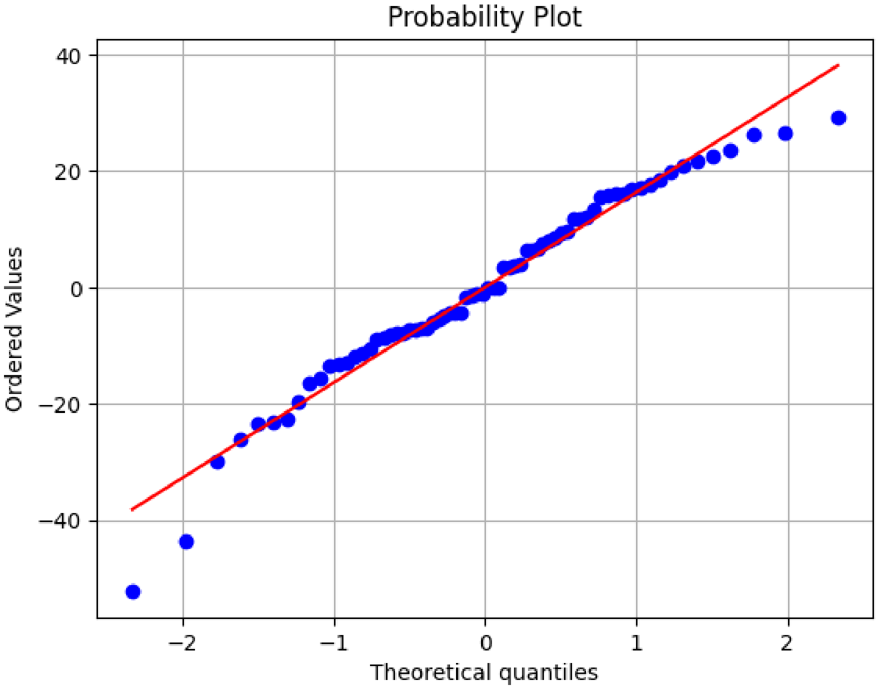


tiny Machine Learning

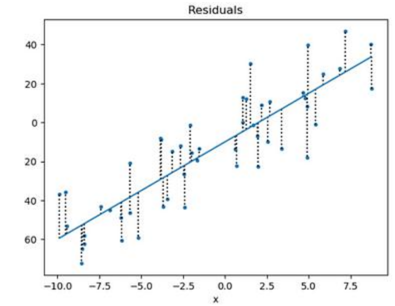


Residuals

```
stats.probplot(residuals, dist="norm", plot=pylab)
plt.grid()
pylab.show()
```

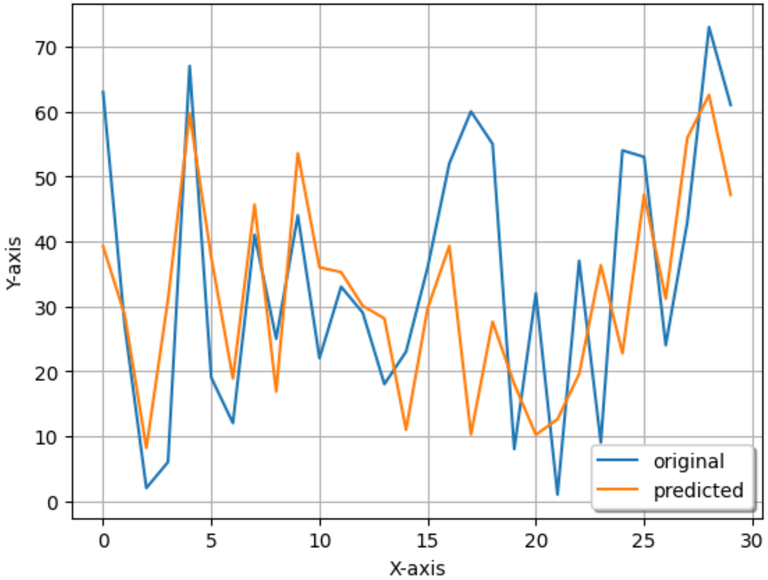


tiny Machine Learning

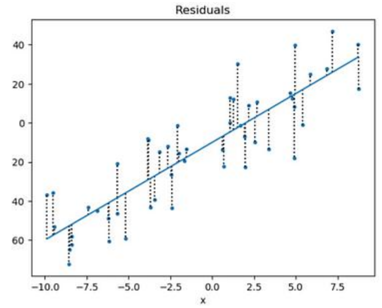


Residuals

```
x_ax = range(len(y_test))
plt.plot(x_ax, y_test, label="original")
plt.plot(x_ax, test_predict, label="predicted")
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.legend(loc='best',fancybox=True, shadow=True)
plt.grid(True)
plt.show()
```



tiny Machine Learning

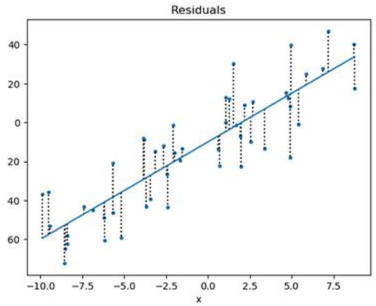


Residuals

```
score = model.score(X_test, y_test)
test_predict = model.predict(X_test)
mse = mean_squared_error(y_test, test_predict)

print("R-squared:", score)
print("MSE: ", mse)
print("RMSE: ", mse*(1/2.0))
```

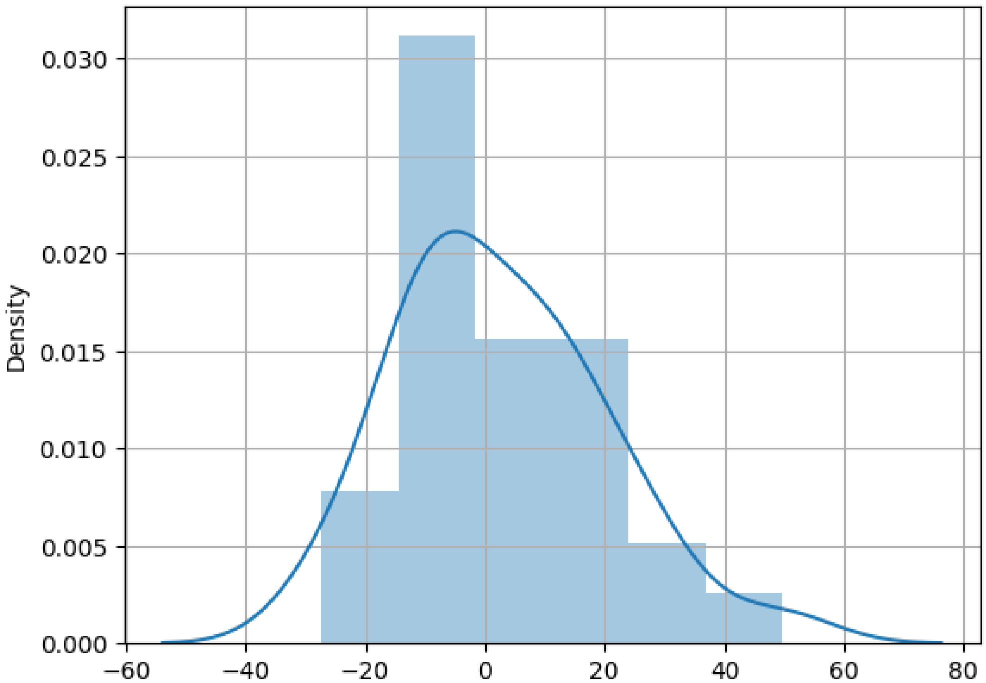
```
R-squared: 0.267072213466814
MSE:  300.75203101864935
RMSE:  150.37601550932467
```

tiny Machine Learning

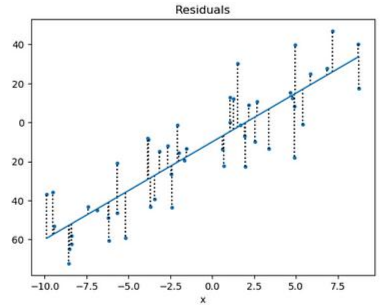


Residuals

```
residuals = y_test-test_predict
sns.distplot(residuals)
plt.grid()
```

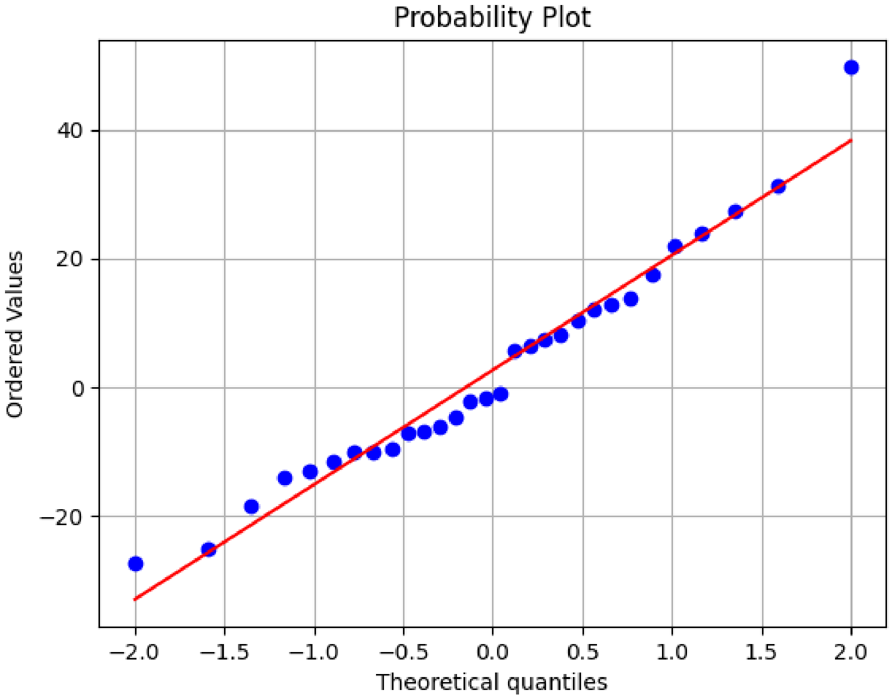


tiny Machine Learning

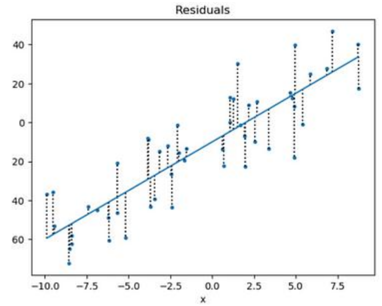


Residuals

```
stats.probplot(residuals, dist="norm", plot=pylab)
plt.grid()
pylab.show()
```



tiny Machine Learning



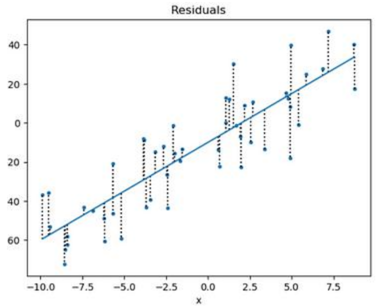
Export & Arduino

```
print(port(model))

with open('.\LinearRegressor.h', 'w') as file:
        file.write(port(model))
```

NOTE: in case of Arduino Compile Errors
In file LinearRegressor.h verify if include is :

#include <cstdarg> => **change to** => #include <stdarg.h>

tiny Machine Learning



Export & Arduino

```
#include "LinearRegressor.h"

Eloquent::ML::Port::LinearRegression LinearRegressor;

void setup()
{
Serial.begin(115200);
}

void loop()
{
float X_1[] = {0.02717829, 0.05068012, 0.01750591, -0.03321323, -0.00707277, 0.04597154,
-0.06549067, 0.07120998, -0.09643495, -0.05906719};
int result_1 = LinearRegressor.predict(X_1);
Serial.print("Result of predict with input X1 (real value = 13):");
Serial.println(result_1);
delay(2000);
}
```

Step #0: Before start

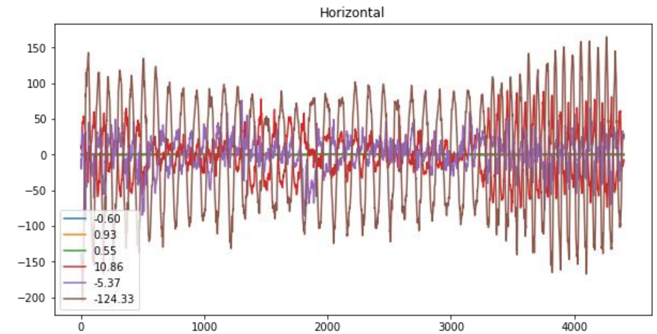
Create a python project and test an example

1. pip install numpy pandas scikit-learn embedded_window micromlgen

```
from micromlgen import port
from sklearn.svm import SVC
from sklearn.datasets import load_iris


if __name__ == '__main__':
    iris = load_iris()
    X = iris.data
    y = iris.target
    clf = SVC(kernel='linear').fit(X, y)
    print(port(clf, classmap={
        0: 'setosa',
        1: 'virginica',
        2: 'versicolor'
    }))
```

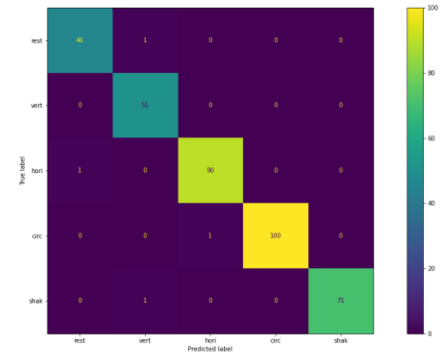
Support Vector Machine

Step #2: Train a Machine Learning model for gesture recognition



Step 2.1 Load data in Python

Load.py



Step 2.2 Reframe to windows

Reframe.py

Step 2.3 Train a Machine learning classifier

Train.py

Step #3 Deploy back to Arduino

The workflow is:

read accelerometer data (the same exact way we did in Step 1)
reframe data into windows and extract features
predict using an algorithm

Step 3.1 Port the Window object to C++

```
# create a Window.h file with the window logic to include in your Arduino sketch with
open("Window.h", "w") as file: file.write(window.port())
```

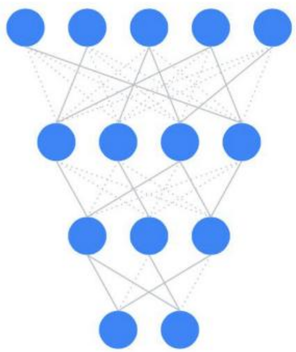
Step 2.2 Reframe to windows

```
from micromlgen import port

with open("Classifier.h", "w") as file:
    file.write(port(clf, classname="Classifier",
                    classmap={0: "rest", 1: "vert", 2: "hori", 3: "circ", 4: "shak"}))
```

Step 3.3 Running in the microcontroller

Run.ino

tiny Machine Learning



How to use deep learning (Ai) | Tensorflow to build tinyML solutions?

1. Load dataset
2. Build the neural network
3. Train
4. Export to C++
5. Run in microcontroller

tiny Machine Learning

Step 1) Load a dataset in Python

```
import numpy as np
from tensorflow.keras import Sequential, layers
from tensorflow.keras.utils import to_categorical
from sklearn.datasets import load_wine
from sklearn.model_selection import train_test_split

# load and split dataset into train, validation, test

X, y = load_your_dataset()
y = to_categorical(y)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=0.3)

input_dim = X_train.shape[1:]
output_dim = y.shape[1]

print('input_dim', input_dim)
print('output_dim', output_dim)
```

Adapt to each dataset

tiny Machine Learning

WARNING:
TensorFlow Lite Micro doesn’t have all operations !!

tiny Machine Learning

Step 2) Train a Neural Network in Python

```
# create and train network
# you can customize the layers as you prefer

nn = Sequential()
nn.add(layers.Dense(units=50, activation='relu', input_shape=input_dim))
nn.add(layers.Dense(units=50, activation='relu'))
nn.add(layers.Dense(output_dim, activation='softmax'))

# use categorical_crossentropy for multi-class classification
nn.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
nn.fit(X_train, y_train, validation_data=(X_valid, y_valid), epochs=100, verbose=0)

print('Accuracy: %.1f' % nn.evaluate(X_test, y_test)[1])
```

Adapt to each dataset

tiny Machine Learning

Step 3) Export from Python to C++

Adapt to each dataset

pip install tinymlgen

```
from tinymlgen import port

# Version 1
tf_model = create_tf_network()
print(port(tf_model))

# Version2
print(port(nn, variable_name='my_model', pretty_print=True, optimize=False))
```

tiny Machine Learning

Step 4) Run in microcontroller

```
#include <EloquentTinyML.h>
#include <eloquent_tinyml/tensorflow.h>

// sine_model.h contains the array you exported from Python with xxd or tinymlgen
#include "model.h"

#define N_INPUTS 1
#define N_OUTPUTS 1
// in future projects you may need to tweak this value: it's a trial and error process
#define TENSOR_ARENA_SIZE 2*1024

Eloquent::TinyML::TensorFlow::TensorFlow<N_INPUTS, N_OUTPUTS, TENSOR_ARENA_SIZE> tf;


void setup() {
   Serial.begin(115200);
   delay(4000);
   tf.begin(model);

   // check if model loaded fine
   if (!tf.isOk()) {
      Serial.print("ERROR: ");
      Serial.println(tf.getErrorMessage());

      while (true) delay(1000);
   }
}
```

tiny Machine Learning

Step 4) Run in a microcontroller

```
void loop() {

        float input[1] = { MPU_data };
        float predicted = tf.predict(input);

        Serial.println(MPU_data);
        Serial.print("predicted: ");
        Serial.println(predicted);
        }

   delay(100);
}
```

?????

Adapt to each dataset