# Perceptron

**Learning Portfolio 3** 



#### Data Set

The data set is a data set retrieved on <a href="kaggle">kaggle</a>. It contains data about Titanic passengers and whether they survived the crash.

The goal of the data set is to predict whether the passengers died or not.

#### [3] data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 891 entries, 0 to 890 Data columns (total 12 columns): Column Non-Null Count Dtype PassengerId 891 non-null int64 Survived 891 non-null int64 Pclass 891 non-null int64 Name 891 non-null object Sex 891 non-null object Age 714 non-null float64 SibSp 891 non-null int64 891 non-null int64 Parch Ticket 891 non-null object float64 Fare 891 non-null Cabin 204 non-null object Embarked 889 non-null object dtypes: float64(2), int64(5), object(5) memory usage: 83.7+ KB



# **Data Preprocessing**

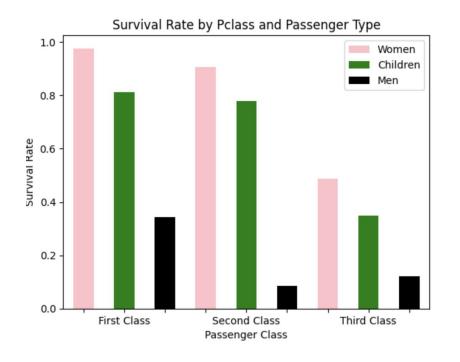
- Missing values in "Age" -> Imputed by clustering
- Missing values in "Embarked" -> Imputed by Mode
- New Feature "Passenger Type" -> Child,
   Women or Men (ordinal)
- "SibSp", "Parch" -> Dichotomous reduction
- Logarithmic transformation and scaling
- One-Hot-Encoding for categorical data

```
# drop not needed data
data = data.drop("Cabin", axis=1)
data = data.drop("Ticket", axis=1)
data = data.drop("Name", axis=1)
# impute passenger age using k-nearest neighbors
from sklearn.impute import KNNImputer
imputer = KNNImputer()
data_num = data.select_dtypes(include=[np.number])
imputer.fit(data_num)
data_new = imputer.transform(data_num)
data["Age"] = data new[:,3]
# impute embarkation point by mode
from sklearn.impute import SimpleImputer
s_imputer = SimpleImputer(strategy="most_frequent")
s_imputer.fit(data)
data new = s imputer.transform(data)
data["Embarked"] = data_new[:,3]
# reduce to boolean attribute
data['SibSp'] = data['SibSp'].apply(lambda x: 0 if x == 0 else 1)
data['Parch'] = data['Parch'].apply(lambda x: 0 if x == 0 else 1)
```



#### **Data Visualization**

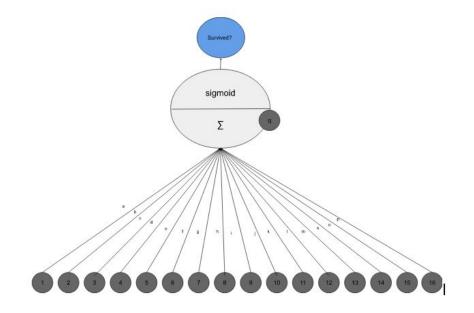
- Women were more likely to survive than children and men
- Thir passenger class was the least likely to survive





# **Training**

- 15 weights (a to p)
- Bias q
- Activation function sigmoid





# **Training**

- Loss function: RMSE
- Learning rate: 1
- Training until loss = previous\_loss
- Local Optimum: 0.369
- 18.29 % wrong predictions on the validation data set

```
# Initializing learning rate
lr = 1e0
def apply step(params):
    # Generating predictions based on input array x, current param set and fur
    preds = f(tensor data, params)
    # Calculating loss function for predictions and target values
    loss = rmse(preds, tensor_label)
    # Calculate gradient for current param set
    loss.backward()
    # Change param set according to learning rate and calculated gradients
    params.data -= lr * params.grad.data
    # Reset gradients for next iteration
    params.grad = None
    # print current loss
    print("loss ")
    print(loss.item())
    return loss.item()
# Initializing parameters for prediction function to seventeen random values
params = torch.randn(17).requires_grad_()
prev_loss = 0
# repeat until local optimum is found
while True:
  loss = apply_step(params)
  if loss == prev loss:
    print("Local Optimum found.")
    break
  else:
    prev loss = loss
```

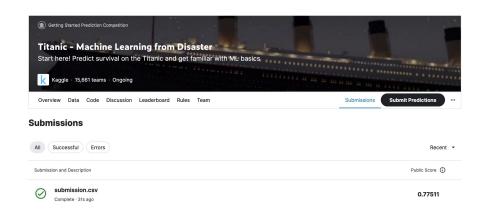
```
[19] preds = f(tensor_data, params)
  incorrect = ((preds.round() - tensor_label).abs()).sum()
  incorrect.item()/tensor_data.shape[0]
```

0.1829405162738496



# **Testing**

- 77.511 % accuracy
- Above average accuracy for models in kaggle





### Kontakt

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