Predicting Credit Card Defaults

W207: Applied Machine Learning

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Dataset and EDA

Default of Credit Card Clients

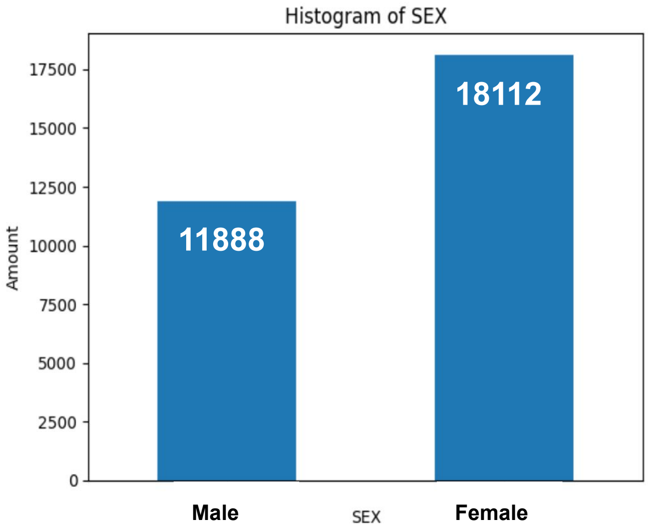
Contains demographic info, credit information, and history of payments and defaults of 30k credit card customers in Taiwan from April to September 2005.

Data source: UCI Machine Learning Repository

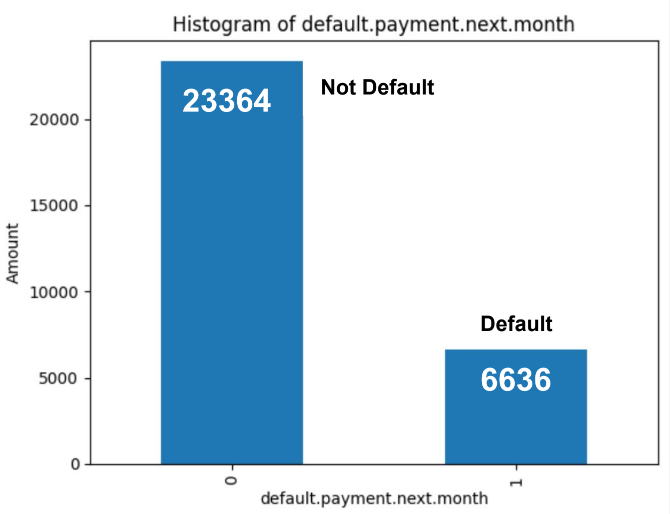
Variables (24 Total) and Description:

- **Client ID**
- **Gender**
- **Education**
- **Marital Status**
- **Age**
- **Credit Limit**
- **Repayment status**
  - Six variables for each month from April-September 2005
  - Categorical value labeled -1 to 9; indicating if account is paid up to date (-1) or number of months delayed (1-9)
- **Amount of bill and payment amount made by month**
  - Numeric; 12 total variables
- **Default status**
  - 1=default, 0=no default

Visualizing the data - Imbalance of categorical features



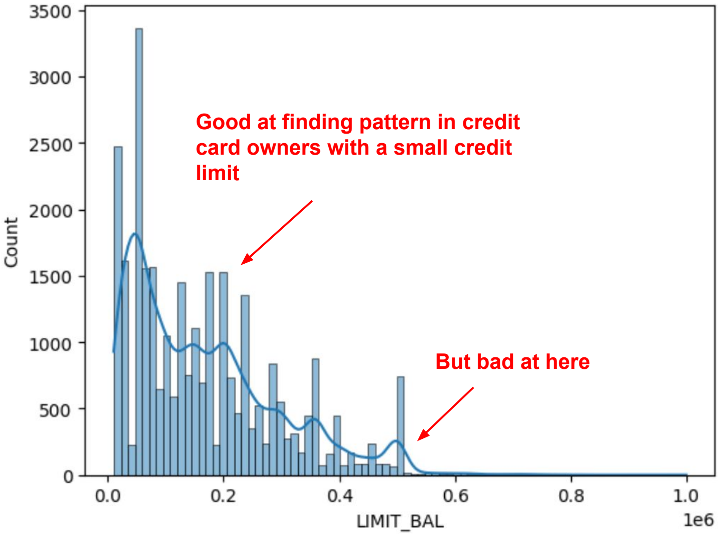
This may induce potential unfairness if the model performs better on Female than Male or that gender is a critical factor of prediction.



The imbalanced target data set might make our model only learn how to identify “non-default” (bad recall)

Goal: balance the data set according to the recall and precision of the model

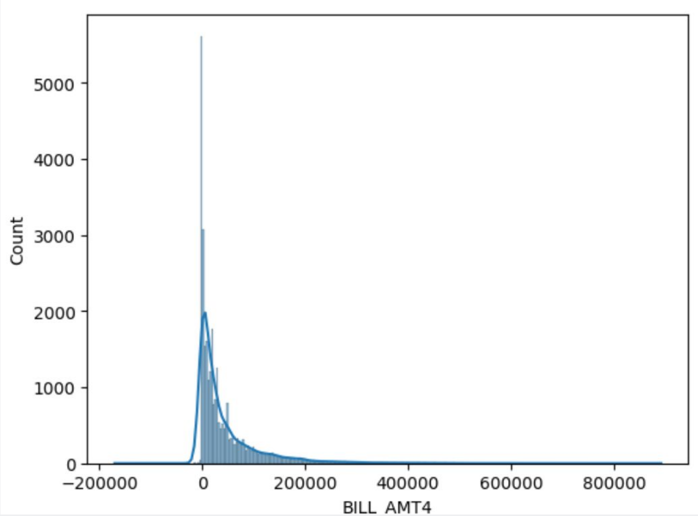
Visualizing the data - Skewness of numerical features



Good at finding pattern in credit card owners with a small credit limit

But bad at here

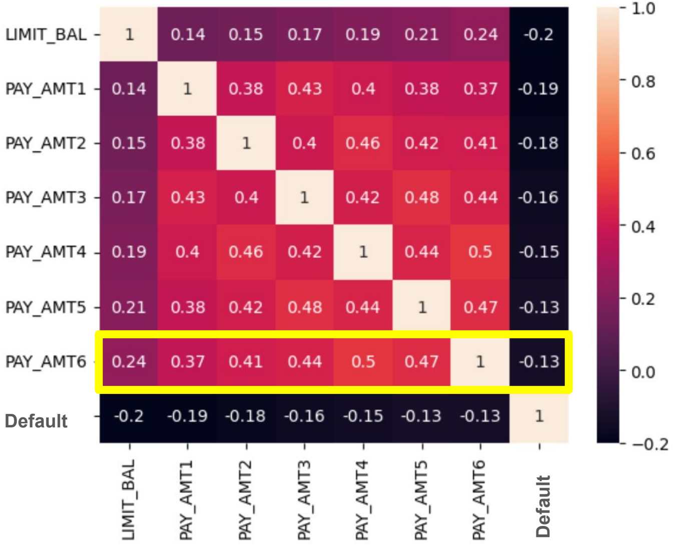
Our model may only learn the left part of the data set with severe right skewness



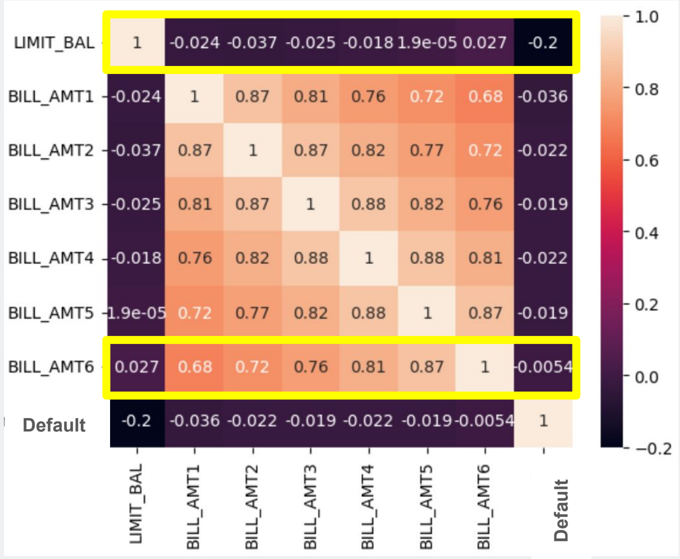
The amount of the bill also has a right skewed distribution.

We first took the log transformation on heavily right skewed features and normalized by the z-score.

Visualizing the data - Collinearity



	LIMIT_BAL	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_AMT5	PAY_AMT6	Default
LIMIT_BAL	1	0.14	0.15	0.17	0.19	0.21	0.24	-0.2
PAY_AMT1	0.14	1	0.38	0.43	0.4	0.38	0.37	-0.19
PAY_AMT2	0.15	0.38	1	0.4	0.46	0.42	0.41	-0.18
PAY_AMT3	0.17	0.43	0.4	1	0.42	0.48	0.44	-0.16
PAY_AMT4	0.19	0.4	0.46	0.42	1	0.44	0.5	-0.15
PAY_AMT5	0.21	0.38	0.42	0.48	0.44	1	0.47	-0.13
PAY_AMT6	0.24	0.37	0.41	0.44	0.5	0.47	1	-0.13
Default	-0.2	-0.19	-0.18	-0.16	-0.15	-0.13	-0.13	1



	LIMIT_BAL	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_AMT6	Default
LIMIT_BAL	1	-0.024	-0.037	-0.025	-0.018	1.9e-05	0.027	-0.2
BILL_AMT1	-0.024	1	0.87	0.81	0.76	0.72	0.68	-0.036
BILL_AMT2	-0.037	0.87	1	0.87	0.82	0.77	0.72	-0.022
BILL_AMT3	-0.025	0.81	0.87	1	0.88	0.82	0.76	-0.019
BILL_AMT4	-0.018	0.76	0.82	0.88	1	0.88	0.81	-0.022
BILL_AMT5	1.9e-05	0.72	0.77	0.82	0.88	1	0.87	-0.019
BILL_AMT6	0.027	0.68	0.72	0.76	0.81	0.87	1	-0.0054
Default	-0.2	-0.036	-0.022	-0.019	-0.022	-0.019	-0.0054	1

There is modest correlation between monthly payments. We may be able to make a prediction based on the repayment status of the first couple of months.

The amount of credit has little correlation with default or bill amounts. Correlation between bill payments month-to-month is relatively strong.

Approach and Model Training

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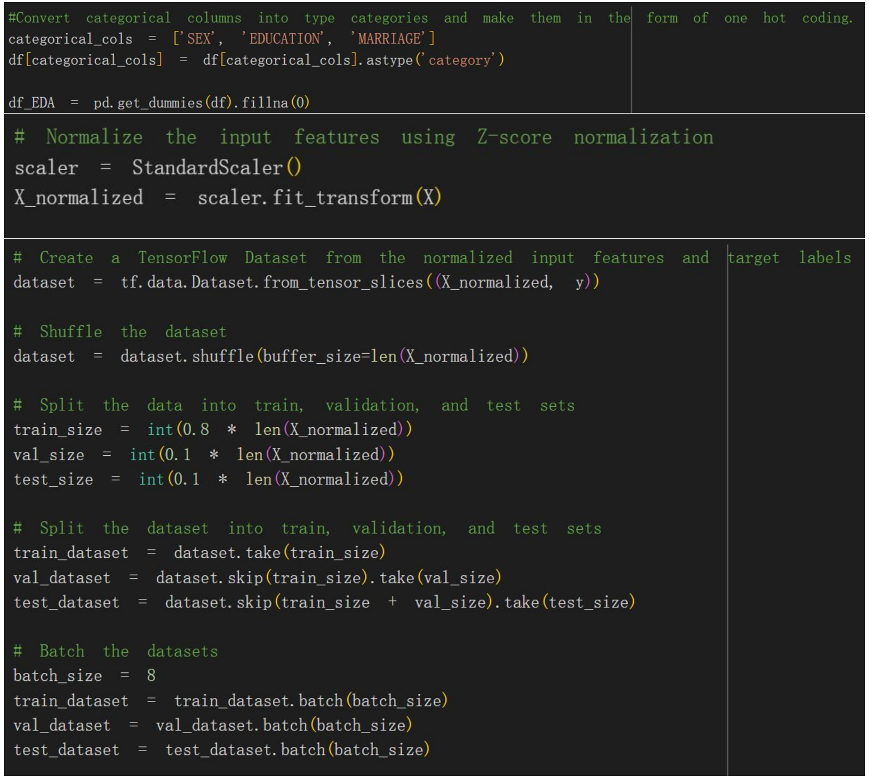
Data Preprocessing and model building

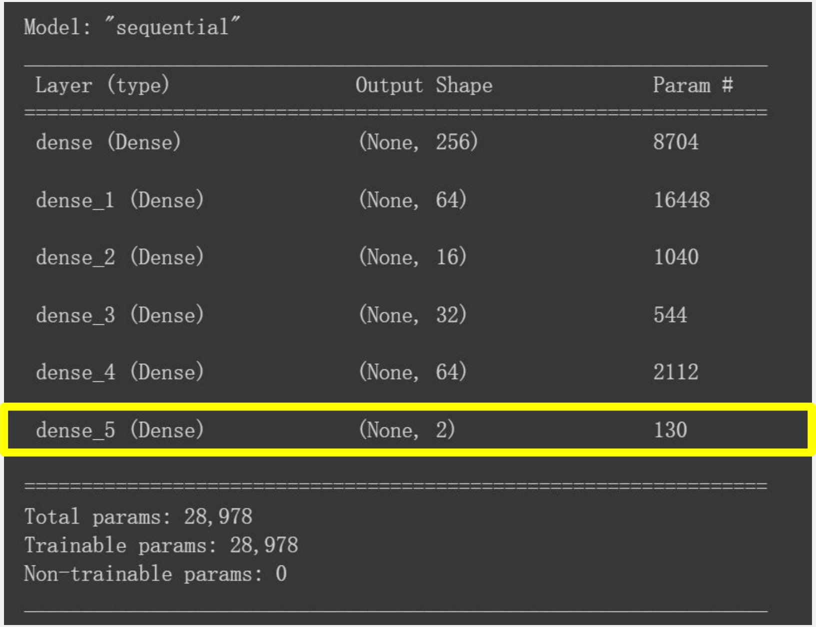


```
#Convert categorical columns into type categories and make them in the form of one hot coding.
categorical_cols = ['SEX', 'EDUCATION', 'MARRIAGE']
df[categorical_cols] = df[categorical_cols].astype('category')

df_EDA = pd.get_dummies(df).fillna(0)
```

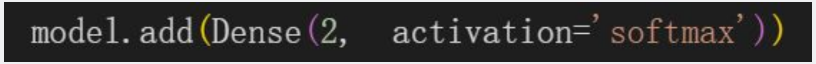
```
# Normalize the input features using Z-score normalization
scaler = StandardScaler()
X_normalized = scaler.fit_transform(X)
```

```
# Create a TensorFlow Dataset from the normalized input features and target labels
dataset = tf.data.Dataset.from_tensor_slices((X_normalized, y))

# Shuffle the dataset
dataset = dataset.shuffle(buffer_size=len(X_normalized))

# Split the data into train, validation, and test sets
train_size = int(0.8 * len(X_normalized))
val_size = int(0.1 * len(X_normalized))
test_size = int(0.1 * len(X_normalized))

# Split the dataset into train, validation, and test sets
train_dataset = dataset.take(train_size)
val_dataset = dataset.skip(train_size).take(val_size)
test_dataset = dataset.skip(train_size + val_size).take(test_size)

# Batch the datasets
batch_size = 8
train_dataset = train_dataset.batch(batch_size)
val_dataset = val_dataset.batch(batch_size)
test_dataset = test_dataset.batch(batch_size)
```

Input shape (8, 33)



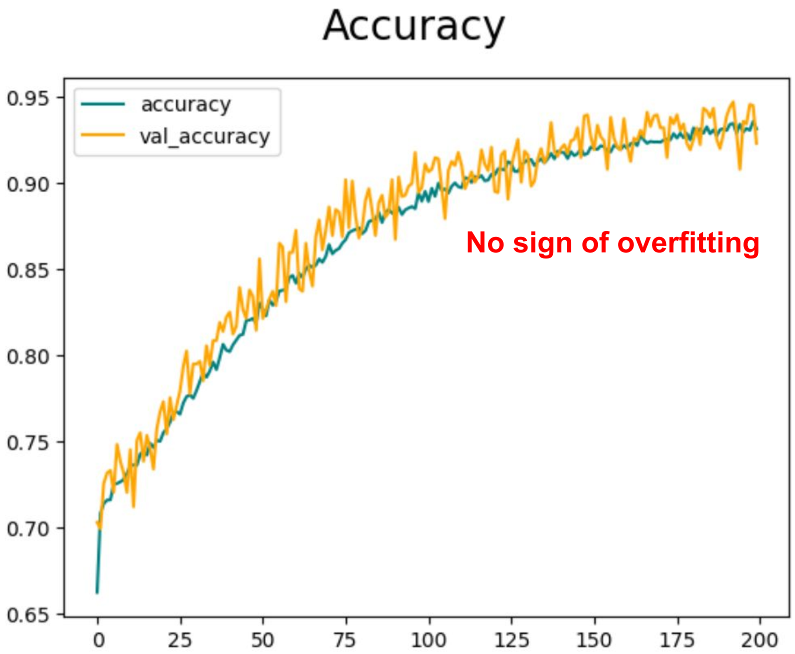
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 256)               8704

 dense_1 (Dense)             (None, 64)                16448

 dense_2 (Dense)             (None, 16)                1040

 dense_3 (Dense)             (None, 32)                544

 dense_4 (Dense)             (None, 64)                2112

 dense_5 (Dense)             (None, 2)                 130

=================================================================
Total params: 28,978
Trainable params: 28,978
Non-trainable params: 0
_________________________________________________________________
```



```
model.add(Dense(2, activation='softmax'))
```

Treated the output layer as multi class classification with two classes instead of binary classification (sigmoid).

Model training (All 33 features)



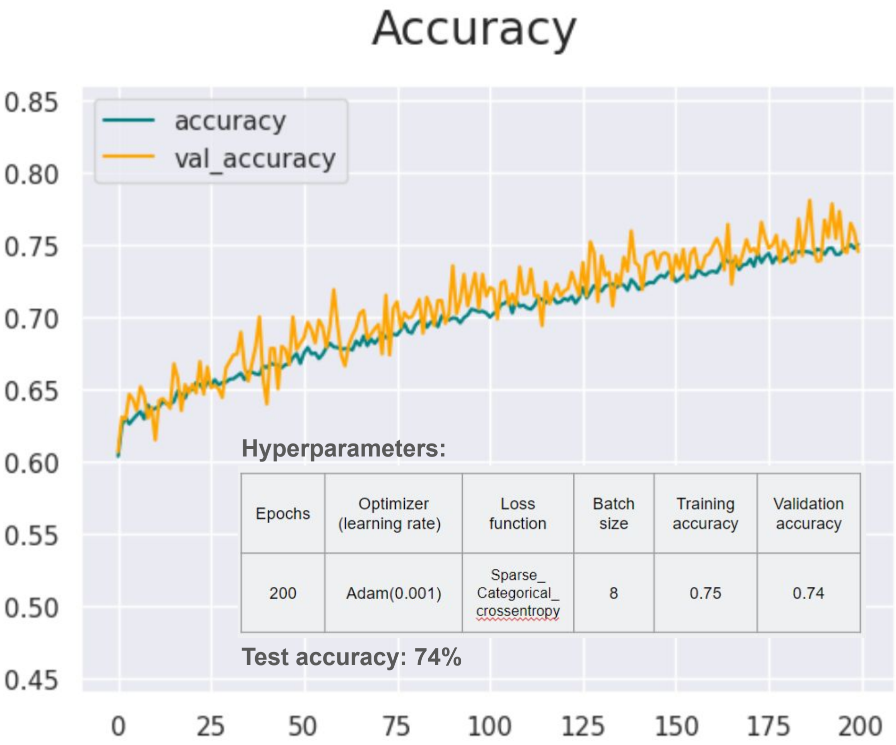
No sign of overfitting

Hyperparameters:

Epochs	Optimizer (learning rate)	Loss function	Batch size	Training accuracy	Validation accuracy
100	Adam(0.01)	Sparse_ Categorical_ crossentropy	16	90%	90%
150	Adam(0.01)		16	92.5%	93%
190	Adam(0.01)		16	93%	93%
200	Adam(0.001)		8	93%	94%

Test accuracy: 93.6%

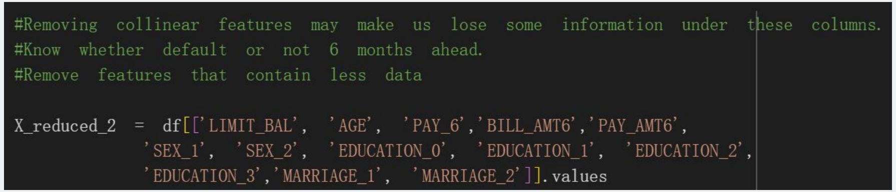
Model training (13 features)



Hyperparameters:

Epochs	Optimizer (learning rate)	Loss function	Batch size	Training accuracy	Validation accuracy
200	Adam(0.001)	Sparse_ Categorical_ crossentropy	8	0.75	0.74

Test accuracy: 74%



```
#Removing  collinear  features  may  make  us  lose  some  information  under  these  columns.
#Know  whether  default  or  not  6  months  ahead.
#Remove  features  that  contain  less  data

X_reduced_2  =  df[[’LIMIT_BAL’,  ’AGE’,  ’PAY_6’,’BILL_AMT6’,’PAY_AMT6’,
             ’SEX_1’,  ’SEX_2’,  ’EDUCATION_0’,  ’EDUCATION_1’,  ’EDUCATION_2’,
             ’EDUCATION_3’,’MARRIAGE_1’,  ’MARRIAGE_2’]].values
```

33 features may be too dense for the model to learn. Furthermore, if we only adapt the payment status of the first month and make a prediction only based on this, our model is predicting default five months ahead which is meaningful in a business context.

Evaluation

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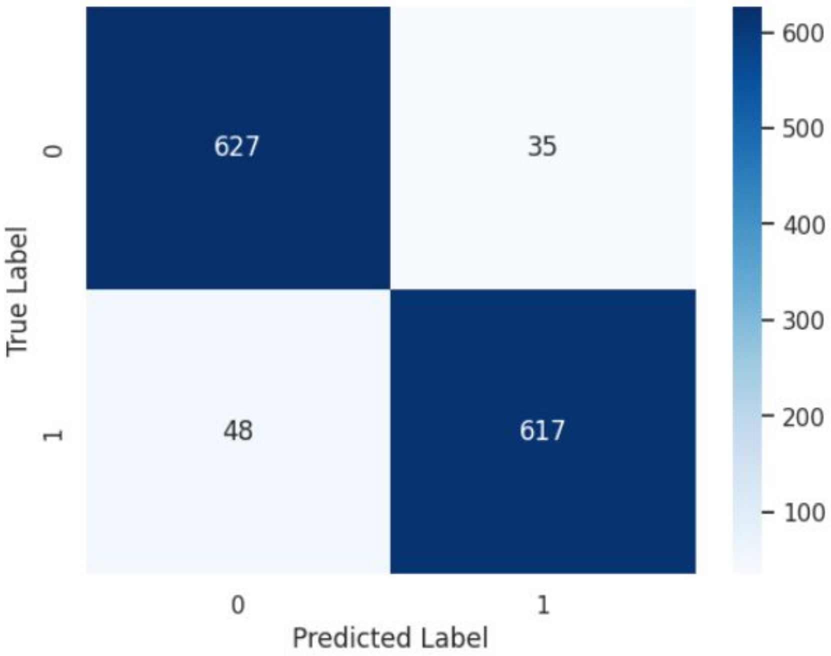
Evaluation of the model (all 33 features) for an imbalanced data set (default)

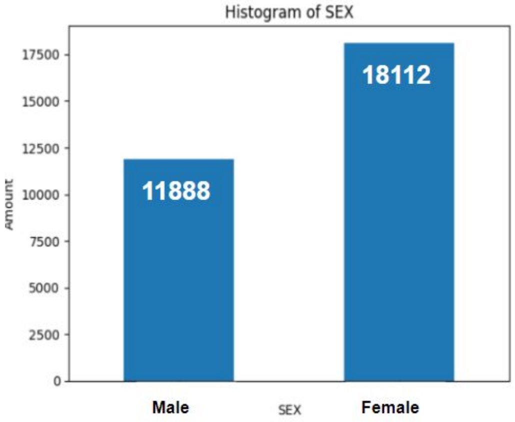


Data set and performance:

Total	Non-Default	Default	Epochs	Test accuracy	Recall	Precision
30000	23364	6636	100	90%	74%	88%
22636	16000	6636	100	90%	78%	89%
16636	10000	6636	100	89.7%	84%	89%
13272	6636	6636	100	89.5%	86%	94%
13272	6636	6636	200	93%	94%	93%

For a given default data example, we can be 94% sure to identify it as default.

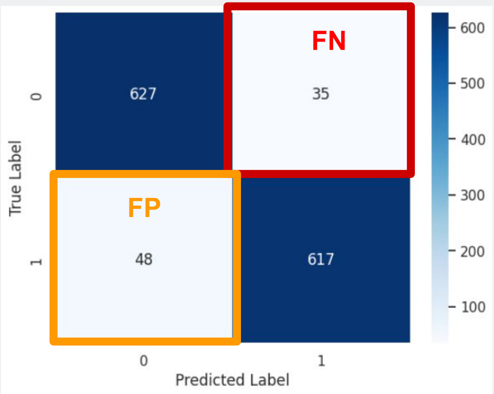
Evaluation of the model (all 33 features) for an imbalanced data set (gender)



We have an imbalanced data set with around 40% male and 60% female credit card users. Our model is likely to learn more from female over male and cause gender bias.

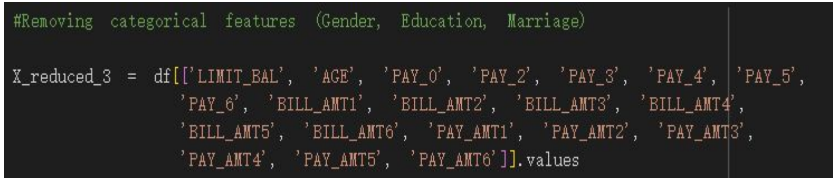
In this case, the false negative rate on both genders is similar to the gender distribution in the data. However, the FP rate of females is slightly higher, which implies for a given default example, females are more likely to be predicted as non-default.

False positive and negative of the gender subgroup



Gender rate	FN_Male	FN_Female	FP_Male	FP_Female
41% male 59% female	16	19	15	33
	45%	55%	31%	69%

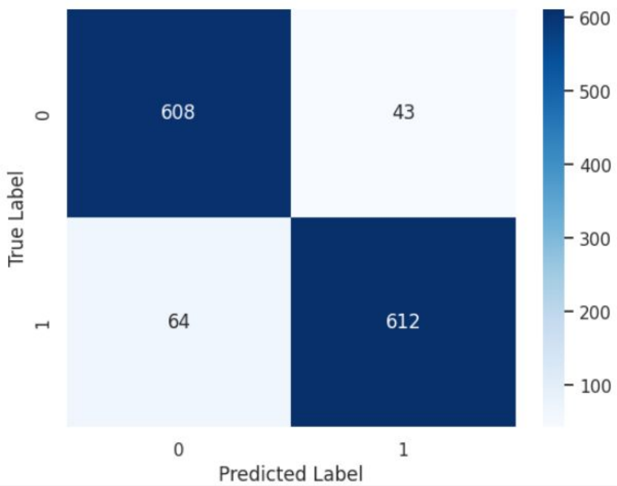
Training and Evaluation of the model - No personal information



```
#Removing  categorical  features  (Gender,  Education,  Marriage)

X_reduced_3  =  df[['LIMIT_BAL',  'AGE',  'PAY_0',  'PAY_2',  'PAY_3',  'PAY_4',  'PAY_5',
                   'PAY_6',  'BILL_AMT1',  'BILL_AMT2',  'BILL_AMT3',  'BILL_AMT4',
                   'BILL_AMT5',  'BILL_AMT6',  'PAY_AMT1',  'PAY_AMT2',  'PAY_AMT3',
                   'PAY_AMT4',  'PAY_AMT5',  'PAY_AMT6']].values
```

Our model makes a prediction based on the users' payment status, and to prevent bias is not using any personal information such as gender, education level, or marital status. We only feed the users' age and their payment status as input features, reducing the feature set from 33 features to 20 features.

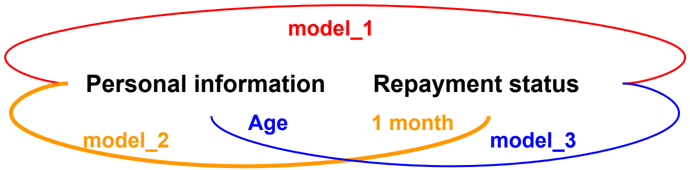


Features	Not Default	Default	Epochs	Test accuracy	Recall	Precision
33	6636	6636	200	93%	94%	93%
20	6636	6636	200	90%	90%	93%

Ensemble
(Bagging: Weighting Average)

So, we have

1. model_1: a comprehensive model with personal information and repayment status (33 features)
2. model_2: a model with personal information and the first month of repayment status to predict 5 months head. (13 features)
3. model_3: a model with only age and repayment status to remove potential bias. (20 features)



For a business scenario we would apply model_3 and boost the accuracy through other models using the ensemble method.

Sample size	Epochs	Weights of models	Test accuracy	Recall	Precision
13272	200	[1,0,0]	93%	94%	93%
13272	200	[0,0,1]	90%	90%	93%
13272	200	[0.2, 0.1, 0.7]	93%	92%	94.1%
13272	200	[0.4, 0.1, 0.5]	95%	95%	95.7%
13272	200	[0.7,0.5,0.6]	95.7%	95.4%	96%

Conclusions

Conclusions

Societal impacts:

The model identifies certain demographics as risky, hence the model can be used to limit credit access to certain demographics, which is unfair and not ethical.

Limitations:

The data spans a short amount of time of 6 months and comes from a specific geography. The model therefore is not taking into consideration the economic environment and it might be inaccurate for other geographies.

A model trained on data from 2005 might not be accurate nearly two decades later.

Key Results and Future Work

- Removing features like gender, level of education, marital status results in a lower but sufficient test accuracy of 90%
- By using ensemble modeling - learning from all previous models - we achieved an accuracy of 95.7% .95.4% recall, and a precision of 96%

Future work:

- Tune hyperparameters, use additional inputs like interest rate, inflation rate in country, number of credit cards owned
- Research if models with local data work better, or is that overfitting?

Contribution and Sources

- **(20%) Code and presentation submission**: Daniel
- **(20%) Dataset and EDA:** Daniel/Ryan
- **(30%) Approach and Models:** Ryan
- **(20%) Tuning and Improvements:** Mehmet
- **(10%) Conclusions and Checklist:** Mehmet

Sources:

- Kaggle
- UCI Machine Learning Repository
- Exploratory Data Analysis With Pandas || Python Machine Learning PT.1 and PT2,3
- https://encord.com/blog/an-introduction-to-balanced-and-imbalanced-datasets-in-machine-learning/
- https://www.analyticsvidhya.com/blog/2015/12/improve-machine-learning-results/
- 214 - Improving semantic segmentation (U-Net) performance via ensemble of multiple trained networks

Team repo: RyanChen12035/W207_Project1_Inonu_Myers_Chen (github.com)