In [1]:
```
import warnings
warnings.simplefilter('ignore')

import re
from time import time
from scipy import stats
import json

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline

from IPython.display import display, Math, Latex
from sklearn.linear_model import Lasso,Ridge,LogisticRegression

from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import confusion_matrix

from sklearn.svm import SVC

from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

%matplotlib inline
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

from sklearn.ensemble import RandomForestClassifier


from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.metrics import make_scorer, roc_auc_score, log_loss, accuracy_s
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import LabelEncoder,MinMaxScaler

from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestClassifier
```

In [2]:
```
from google.colab import drive
drive.mount("/content/gdrive")
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, ca
ll drive.mount("/content/gdrive", force_remount=True).
```

In [3]:
```
import pandas as pd
A_train = pd.read_csv('/content/gdrive/My Drive/final_features.csv')
```

In [4]:
```
A_train.head()
```

Out[4]:

	SK_ID_CURR	DAYS_CREDIT	DAYS_ENDDATE_FACT	AMT_CREDIT_SUM	DAYS_CREDIT_UP
0	100002	-1043.0	-967.0	40761.0	-
1	100010	-1939.5	-1138.0	495000.0	-
2	100019	-495.0	NaN	360000.0	
3	100032	-1169.5	-662.0	331875.0	-
4	100033	-195.0	NaN	675000.0	-

5 rows × 82 columns

In [5]:
```
A_train.columns
```

Out[5]:
```
Index(['SK_ID_CURR', 'DAYS_CREDIT', 'DAYS_ENDDATE_FACT', 'AMT_CREDIT_SUM',
       'DAYS_CREDIT_UPDATE', 'MONTHS_BALANCE', 'AMT_CREDIT_SUM_LIMIT',
       'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
       'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT',
       'AMT_ANNUITY_x', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE',
       'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
       'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH',
       'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'FLAG_MOBIL'
,
       'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FLAG_PHONE'
,
       'FLAG_EMAIL', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROCESS_START',
       'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION',
       'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION',
       'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY',
       'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'EXT_SOURCE_2',
       'EXT_SOURCE_3', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE
',
       'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
       'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3',
       'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5', 'FLAG_DOCUMENT_6',
       'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9',
       'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12',
       'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15',
       'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17', 'FLAG_DOCUMENT_18',
       'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21',
       'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
       'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
       'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR',
       'CREDIT_INCOME_PCT', 'CREDIT_TERM_PCT', 'DAYS_EMPLOYED_PCT',
       'ANNUITY_INCOME_PCT'],
      dtype='object')
```

In [6]:
```python
y = A_train['TARGET']
X = A_train.drop(['SK_ID_CURR','TARGET'], axis = 1)
```

In [7]:
```python
application_null_vals = X.isna().sum().reset_index().rename(columns={'index'
application_null_vals['percentage_cnt'] = application_null_vals['null_count'
application_null_vals = application_null_vals[application_null_vals['percent
application_null_vals
```

Out[7]:

	column_name	null_count	percentage_cnt
0	DAYS_CREDIT	0	0.000000
1	DAYS_ENDDATE_FACT	11441	12.397061
2	AMT_CREDIT_SUM	0	0.000000
3	DAYS_CREDIT_UPDATE	0	0.000000
4	MONTHS_BALANCE	0	0.000000
...	...	...	...
75	AMT_REQ_CREDIT_BUREAU_YEAR	0	0.000000
76	CREDIT_INCOME_PCT	0	0.000000
77	CREDIT_TERM_PCT	11	0.011919
78	DAYS_EMPLOYED_PCT	0	0.000000
79	ANNUITY_INCOME_PCT	11	0.011919

80 rows × 3 columns

In [8]:
```
application_null_vals['column_type'] = application_null_vals['column_name'].
application_null_vals[application_null_vals['percentage_cnt'] > 0]
```

Out[8]:

	column_name	null_count	percentage_cnt	column_type
1	DAYS_ENDDATE_FACT	11441	12.397061	float64
13	AMT_ANNUITY_x	11	0.011919	float64
14	AMT_GOODS_PRICE	2	0.002167	float64
43	EXT_SOURCE_2	24	0.026006	float64
44	EXT_SOURCE_3	5883	6.374610	float64
77	CREDIT_TERM_PCT	11	0.011919	float64
79	ANNUITY_INCOME_PCT	11	0.011919	float64

In [9]:
```
test_feature = A_train[application_null_vals['column_name'].tolist() + ['TAR
test_feature['NAME_TYPE_SUITE'].fillna('Other_C', inplace=True)
test_feature.head(7)
```

Out[9]:

	DAYS_CREDIT	DAYS_ENDDATE_FACT	AMT_CREDIT_SUM	DAYS_CREDIT_UPDATE	MONTH
0	-1043.0	-967.0	40761.0	-758.0	
1	-1939.5	-1138.0	495000.0	-578.0	
2	-495.0	NaN	360000.0	-26.5	
3	-1169.5	-662.0	331875.0	-520.5	
4	-195.0	NaN	675000.0	-169.0	
5	-1552.0	-1492.0	78907.5	-1492.0	
6	-1904.0	-1323.0	166860.0	-1320.0	

7 rows × 81 columns

In [10]:
```
col_list =application_null_vals[application_null_vals['null_count'] != 0].re
for col_idx in col_list:
    if 'AMT_REQ_CREDIT' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)
for col_idx in col_list:
    if 'CNT_SOCIAL_CIRCLE' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)
for col_idx in col_list:
    if 'CNT_FAM_MEMBERS' in col_idx:
        print("null values replaced with median: {}".format(col_idx))
        test_feature[col_idx].fillna(test_feature[col_idx].median(),inplace=
for col_idx in col_list:
    if 'DAYS_ENDDATE_FACT' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)

for col_idx in col_list:
    if 'AMT_ANNUITY_x' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)

for col_idx in col_list:
    if 'CREDIT_TERM_PCT' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)
for col_idx in col_list:
    if 'ANNUITY_INCOME_PCT' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)
for col_idx in col_list:
    if 'EXT_SOURCE_3' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)

for col_idx in col_list:
    if 'EXT_SOURCE_2' in col_idx:
        print("null values replaced with 0: {}".format(col_idx))
        test_feature[col_idx].fillna(0,inplace=True)
```

```
null values replaced with 0: DAYS_ENDDATE_FACT
null values replaced with 0: AMT_ANNUITY_x
null values replaced with 0: CREDIT_TERM_PCT
null values replaced with 0: ANNUITY_INCOME_PCT
null values replaced with 0: EXT_SOURCE_3
null values replaced with 0: EXT_SOURCE_2
```

In [11]:
```
def to_fill_category_value(df_object):
    if df_object['AMT_GOODS_PRICE'] != np.inf:
        return df_object['AMT_GOODS_PRICE']

    else:
        return A_train[A_train['NAME_FAMILY_STATUS']==df_object['NAME_FAMILY

for col_idx in col_list:
    test_feature['AMT_GOODS_PRICE'] = test_feature['AMT_GOODS_PRICE'].fillna
    if 'AMT_GOODS_PRICE' in col_idx:
        print("filled with category median is: {}".format(col_idx))
        test_feature['AMT_GOODS_PRICE'] = test_feature.apply(lambda df_objec
```

```
filled with category median is: AMT_GOODS_PRICE
```

In [12]:
```
test_null_data = test_feature.isna().sum().reset_index().rename(columns={'in
test_null_data['percentage_cnt'] = test_null_data['null_count']/len(test_fea
test_null_data = test_null_data[test_null_data['percentage_cnt']<= 30]
test_null_data['column_type'] = test_null_data['column_name'].apply(lambda x
test_null_data[test_null_data['percentage_cnt'] > 0]
```

Out[12]:

column_name	null_count	percentage_cnt	column_type

In [13]:
```
test_feature.isna().sum()
```

Out[13]:
```
DAYS_CREDIT            0
DAYS_ENDDATE_FACT      0
AMT_CREDIT_SUM         0
DAYS_CREDIT_UPDATE     0
MONTHS_BALANCE         0
                      ..
CREDIT_INCOME_PCT      0
CREDIT_TERM_PCT        0
DAYS_EMPLOYED_PCT      0
ANNUITY_INCOME_PCT     0
TARGET                 0
Length: 81, dtype: int64
```

In [14]:
```
test_feature.shape
```

Out[14]:
```
(92288, 81)
```

Deep learning from here

In [15]:
```
from numpy import vstack
from pandas import read_csv
from torch import Tensor
import torch
import torch.nn as nn

from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
from torch.utils.data import DataLoader
from torch.utils.data import Dataset
from torch.utils.data import random_split


from torch.nn.init import kaiming_uniform_
from sklearn.metrics import make_scorer, roc_auc_score
from torch.nn.init import xavier_uniform_

from torch.utils.tensorboard import SummaryWriter
writer = SummaryWriter()
from sklearn.metrics import mean_squared_error
import math
Stand_scaler = StandardScaler()

from torch.nn import Linear
from torch.nn import ReLU
from torch.nn import Sigmoid
from torch.optim import SGD
from torch.nn import MSELoss
from torch.nn import BCELoss, BCEWithLogitsLoss
from torch.nn import Module
```

In [16]:
```
int_test_var= test_feature.select_dtypes(include='int64')
float_test_var = test_feature.select_dtypes(include='float64')
num_test_var = list(pd.concat([int_test_var,float_test_var], axis=1))
cat_test_var = list(test_feature.select_dtypes(include='object'))
```

In [17]:
```
application_train_target = pd.DataFrame({'TARGET':test_feature['TARGET']})
```

In [18]:
```
test_feature.shape
```

Out[18]:
```
(92288, 81)
```

In [19]:
```
categ_df = test_feature[cat_test_var]
```

In [20]:
```
categ_df = pd.get_dummies(categ_df,drop_first=True)
number_df = test_feature[num_test_var]
input_features = pd.merge(number_df, categ_df, left_index=True, right_index=
input_colums = input_features.columns
application_train = pd.DataFrame(input_features.loc[:, input_features.column
```

In [21]:
```
application_train['TARGET'] = application_train_target
```

In [22]:
```
X = application_train[input_colums]
len(X.columns.tolist())
```

Out[22]:
```
161
```

In [23]:
```
y = application_train['TARGET']
```

In [24]:
```
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.25, r
```

In [25]:
```
X_train
```

Out[25]:

	CNT_CHILDREN	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_ID_PUBLISH	FLAG_MOBIL	F
59882	0	-15477	-933	-4933	1	
62111	1	-19669	365243	-3128	1	
21429	0	-13442	-297	-1369	1	
66558	0	-20107	-2379	-3574	1	
67388	1	-12520	-842	-4189	1	
...	...	...	...	...	...	
54578	1	-9757	-3041	-2380	1	
56760	0	-9071	-1458	-1492	1	
80037	1	-17040	-3007	-575	1	
30727	0	-10456	-1953	-3131	1	
11590	2	-13272	-297	-4735	1	

69216 rows × 161 columns

1st Neural Architecture

In [26]:
```
class MultiLayerProc1(Module):
    def __init__(self, total_inputs):
        super(MultiLayerProc1, self).__init__()
        self.hiddenlayer1 = Linear(total_inputs, 55)
        self.hiddenlayer2 = Linear(55, 15)
        self.hiddenlayer3 = Linear(15, 5)
        self.hiddenlayer4 = Linear(5, 1)
        kaiming_uniform_(self.hiddenlayer1.weight, nonlinearity='relu')
        kaiming_uniform_(self.hiddenlayer2.weight, nonlinearity='relu')
        kaiming_uniform_(self.hiddenlayer3.weight, nonlinearity='relu')
        xavier_uniform_(self.hiddenlayer4.weight)
        self.actfunc1 = ReLU()
        self.actfunc2 = ReLU()
        self.actfunc3 = ReLU()
        self.actfunc4 = Sigmoid()
    def forward(self, X):
        X = self.actfunc1(self.hiddenlayer1(X))
        X = self.actfunc2(self.hiddenlayer2(X))
        X = self.actfunc3(self.hiddenlayer3(X))
        X = self.actfunc4(self.hiddenlayer4(X))
        return X
```

In [27]:
```
model=MultiLayerProc1(161)
```

In [28]:
```
class Class_Data(Dataset):

    def __init__(self, X_data, y_data):
        self.X_data = X_data
        self.y_data = y_data

    def __getitem__(self, ind):
        return self.X_data[ind], self.y_data[ind]

    def __len__ (self):
        return len(self.X_data)

train_data = Class_Data(torch.Tensor(X_train.values),
                       torch.Tensor(y_train.values))



test_data = Class_Data(torch.Tensor(X_test.values),torch.Tensor(y_test.value

batch_size = 100
n_epochs = 40
batch_no = len(X_train) // batch_size

train_loader = DataLoader(dataset=train_data, batch_size=100, shuffle=True)
test_loader = DataLoader(dataset=test_data, batch_size=100)
```

In [29]:
```
criteria = BCEWithLogitsLoss()
optim = SGD(model.parameters(), lr=0.0001, momentum=0.9)
# enumerate epochs
for epoch in range(n_epochs):
    for i, (inputs, targets) in enumerate(train_loader):
        optim.zero_grad()
        yhat = model(inputs)
        targets = targets.unsqueeze(1)
        # calculate loss
        loss = criteria(yhat, targets)
        # plotting on tensorboard
        writer.add_scalar("Loss/train", loss, epoch)
        loss.backward()
        optim.step()
```

In [50]:
```
predictions, actuals = list(), list()
for inputs, targets in test_loader:
    yhat = model(inputs)
    yhat = yhat.detach().numpy()
    actual = targets.numpy()
    actual = actual.reshape((len(actual), 1))
    yhat = yhat.round()
    predictions.append(yhat)
    actuals.append(actual)
predictions, actuals = vstack(predictions), vstack(actuals)
acc = accuracy_score(actuals, predictions)
auc = roc_auc_score(actuals, predictions)
```

In [31]:
```
try: experimentLog
except : experimentLog = pd.DataFrame(columns=["Dataset","Learning rate", "E
experimentLog.loc[len(experimentLog)] =["HCDR", 0.0001, n_epochs, 4, acc, au

experimentLog
```

Out[31]:

	Dataset	Learning rate	Epochs	No_Hidden_layers	Accuracy_score	AUC-ROC	Description
0	HCDR	0.0001	40	4	0.919036	0.742876	Multi layer perceptron exp 1

2nd Neural Architecture

In [51]:
```
class MultiLayerProc2(Module):
    def __init__(self, n_inputs):
        super(MultiLayerProc2, self).__init__()
        self.hiddenlayer1 = Linear(n_inputs, 25)
        self.hiddenlayer2 = Linear(25, 12)
        self.hiddenlayer3 = Linear(12, 1)
        kaiming_uniform_(self.hiddenlayer1.weight, nonlinearity='relu')
```

```
        kaiming_uniform_(self.hiddenlayer2.weight, nonlinearity='relu')
        xavier_uniform_(self.hiddenlayer3.weight)
        self.actfunc1 = ReLU()
        self.actfunc2 = ReLU()
        self.actfunc3 = Sigmoid()

    def forward(self, X):
        X = self.actfunc1(self.hiddenlayer1(X))
        X = self.actfunc2(self.hiddenlayer2(X))
        X = self.actfunc3(self.hiddenlayer3(X))
        return X
model=MultiLayerProc2(161)

class Class_Data(Dataset):

    def __init__(self, X_data, y_data):
        self.X_data = X_data
        self.y_data = y_data

    def __getitem__(self, ind):
        return self.X_data[ind], self.y_data[ind]

    def __len__ (self):
        return len(self.X_data)

train_data = Class_Data(torch.Tensor(X_train.values),
                       torch.Tensor(y_train.values))



test_data = Class_Data(torch.Tensor(X_test.values),torch.Tensor(y_test.value


batch_size = 100
n_epochs = 28
batch_no = len(X_train) // batch_size

train_loader = DataLoader(dataset=train_data, batch_size=32, shuffle=True)
test_loader = DataLoader(dataset=test_data, batch_size=512)
criteria = BCELoss()
optim = SGD(model.parameters(), lr=0.0011, momentum=0.99)
for epoch in range(n_epochs):
    for i, (inputs, targets) in enumerate(train_loader):
        optim.zero_grad()
        yhat = model(inputs)
        targets = targets.unsqueeze(1)
        loss = criteria(yhat, targets)
        writer.add_scalar("Loss/train", loss, epoch)
        loss.backward()
        optim.step()
predictions, actuals = list(), list()
yhat = list()
predictions, actuals = list(), list()
```

```
for i, (inputs, targets) in enumerate(test_loader):
    yhat = model(inputs)
    yhat = yhat.detach().numpy()
    actual = targets.numpy()
    actual = actual.reshape((len(actual), 1))
    yhat = yhat.round()
    predictions.append(yhat)
    actuals.append(actual)
predictions, actuals = vstack(predictions), vstack(actuals)
acc = accuracy_score(actuals, predictions)
auc = roc_auc_score(actuals, predictions)
```

In [33]:
```
try: experimentLog
except : experimentLog = pd.DataFrame(columns=["Dataset","Learning rate", "E
experimentLog.loc[len(experimentLog)] =["HCDR", 0.0011, n_epochs, 3, acc, au

experimentLog
```

Out[33]:

	Dataset	Learning rate	Epochs	No_Hidden_layers	Accuracy_score	AUC-ROC	Description
0	HCDR	0.0001	40	4	0.919036	0.742876	Multi layer perceptron exp 1
1	HCDR	0.0011	28	3	0.920033	0.742862	Multi layer perceptron exp 2

Tensor board

In [34]:
```
# %load_ext tensorboard
# %tensorboard --logdir runs
```

Test dataset preparation

In [35]:
```
application_test = pd.read_csv('/content/gdrive/My Drive/application_test.cs
```

In [36]:
```
application_test
```

Out[36]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_
0	100001	Cash loans	F	N	
1	100005	Cash loans	M	N	
2	100013	Cash loans	M	Y	
3	100028	Cash loans	F	N	
4	100038	Cash loans	M	Y	
...	...	...	...	...	
48739	456221	Cash loans	F	N	
48740	456222	Cash loans	F	N	
48741	456223	Cash loans	F	Y	
48742	456224	Cash loans	M	N	
48743	456250	Cash loans	F	Y	

48744 rows × 121 columns

In [37]:
```
application_test['AMT_CREDIT_TO_ANNUITY_RATIO'] = application_test['AMT_CRED
```

In [38]:
```
application_test['Tot_EXTERNAL_SOURCE'] = application_test['EXT_SOURCE_2'] +
application_test['Salary_to_credit'] = application_test['AMT_INCOME_TOTAL']/
application_test['Annuity_to_salary_ratio'] = application_test['AMT_ANNUITY'
```

In [39]:
```
int_x= application_test.select_dtypes(include='int64')
float_x = application_test.select_dtypes(include='float64')
num_attribs = list(pd.concat([int_x,float_x], axis=1))
cat_attribs = list(application_test.select_dtypes(include='object'))
```

In [40]:
```

le_dict = {}
for col in application_test.columns.tolist():
    if application_test[col].dtype == 'object':
        le = LabelEncoder()
        application_test[col] = application_test[col].fillna("NULL")
        application_test[col] = le.fit_transform(application_test[col])
        le_dict['le_{}'.format(col)] = le
```

In [41]:
```
application_test.head()
```

Out[41]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REA
0	100001	0	0	0	
1	100005	0	1	0	
2	100013	0	1	1	
3	100028	0	0	0	
4	100038	0	1	1	

5 rows × 125 columns

In [42]:
```
scaler = MinMaxScaler()

application_test = application_test.values
```

In [43]:
```
application_test = scaler.fit_transform(application_test)
application_test_dl = DataLoader(application_test, batch_size=32, shuffle=Fa
application_test_dl
```

Out[43]:
```
<torch.utils.data.dataloader.DataLoader at 0x7fd606c366a0>
```

In [52]:
```
for i, (inputs, targets) in enumerate(test_loader):
    yhat = model(inputs)
    yhat = yhat.detach().numpy()
    actual = targets.numpy()
    actual = actual.reshape((len(actual), 1))
    yhat = yhat.round()
    np.append(predictions,yhat,axis = 0)
    np.append(actuals,actual,axis = 0)
    #predictions.append(yhat)
    #actuals.append(actual)
predictions, actuals = vstack(predictions), vstack(actuals)

# calculate accuracy
acc = accuracy_score(actuals, predictions)
auc = roc_auc_score(actuals, predictions)
```

Write Up for Phase 4

PROJECT MEMBERS:

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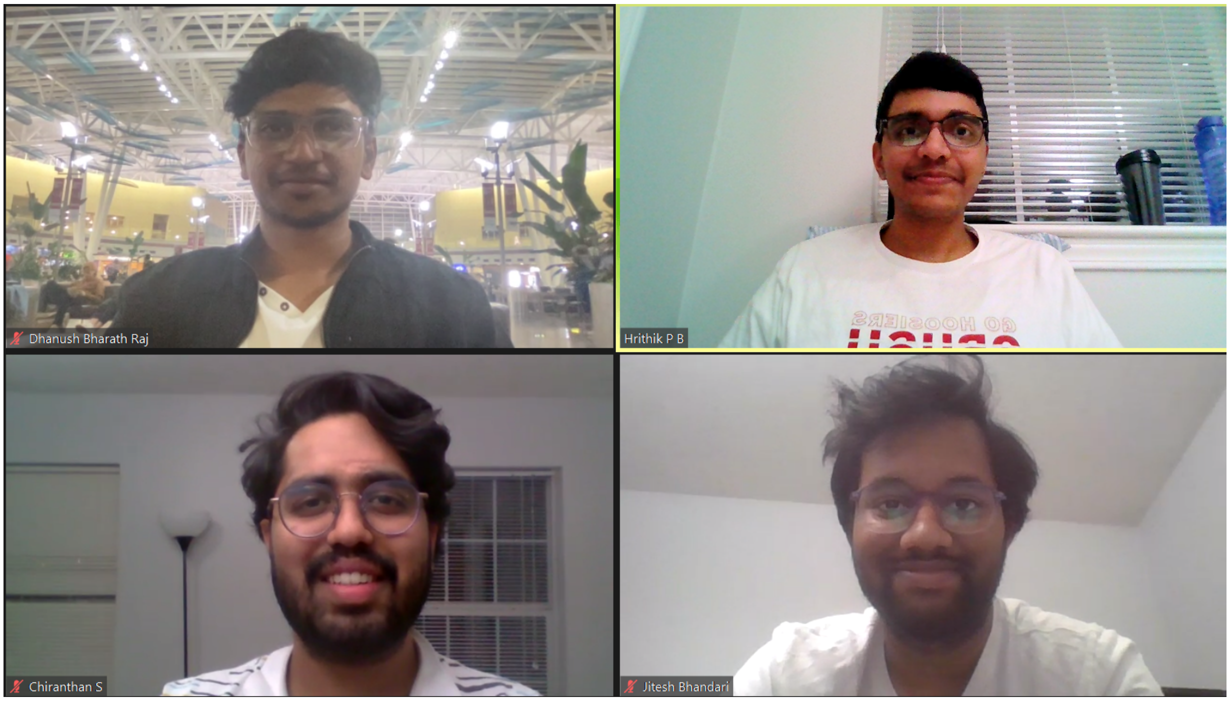
Jitesh Bhandari - jitbhand@iu.edu

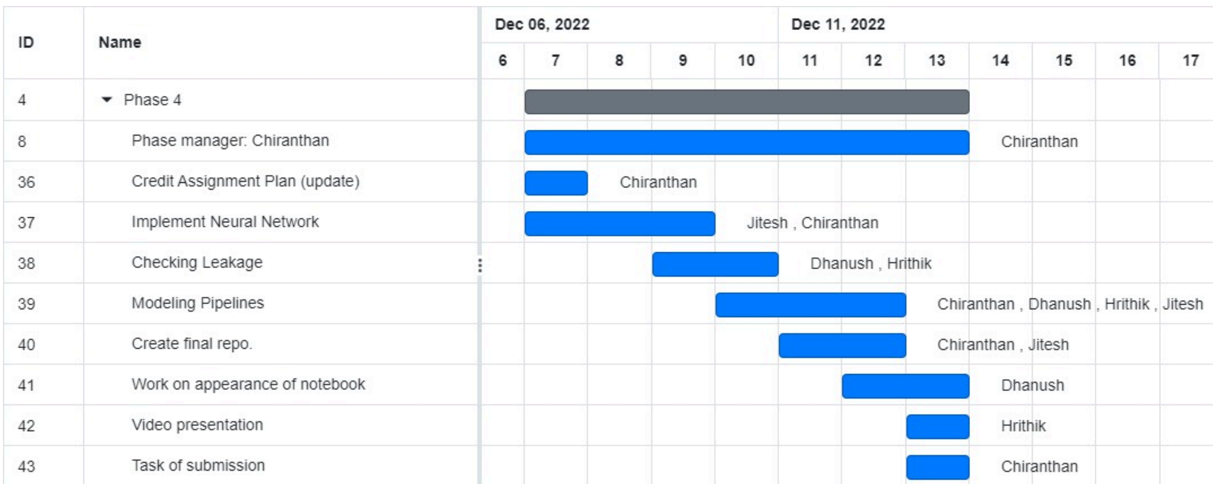
Hrithik PB - hripb@iu.edu

Dhanush Bharath Raj - dbraj@iu.edu



Phase leader and credit assignment plan

Phase	Contributors	Description of Contribution
Phase 4	Chiranthan	Phase leader
Phase 4	Jitesh Bhandari	Implement Neural Network, Creating final repository
Phase 4	Hrithik P B	Video presentation planning, Checking Leakage
Phase 4	Dhanush B Raj	Checking Leakage, Appearance of Notebook
Phase 4	Chiranthan	Implement Neural Network, Planning credit assignment, Creating final repository



Credit Assignment Plan (Table) - Phase 4

Name	Task	Task Description
Chiranthan	Credit Assignment plan	Assigning credits for all the members in the team
	Implement Neural Network	Continuing more in depth research on EDA
	Creating final repo	Implementing the Discussed Algorithms
Hrithik P B	Video presentation planning	Exploring Visual Analaysis
	Checking Leakage	Implementing the Discussed Algorithms
Jitesh	Implement Neural Network	fine tuning the model
	Creating final repo	Making final
Dhanush	Checking Leakage	Joining the tables to engineer new features
	Appearance of Notebook	Compiling the whole notebook in a presentable manner

Project Abstract

In phase 4, our primary objective is to implement Neural Network architecture for the HCDR project. Phase 4 initial phase focuses on designing different neural network architectures and checking for the presenece of any data leakage. The dataset considered for this phase is the one we merged from different datasets available and by fine tuning it by dropping trivial attributes. We intend to build 3 different neural networks by adding or removing hidden layers and the weights associated with it. Further we plan to analyse our accuracy of our model by adjusting epoch, batch size and activation function.

In the entire project, we have used kaggle datasets to perform exploratory data analysis, create machine learning pipelines, and evaluate models according to a variety of criteria before deploying a model. As part of this study, we used a variety of traditional machine learning methods, including Logistic Regression, Random Forest Classifier, XGBoost, to determine with accuracy if a person qualifies for a mortgage. A deep learning model was also set up. We developed a machine learning model for binary classification using Pytorch. A model was created, trained, and evaluated as well.

Project Description

There are 7 different sources of data:

application_train/application_test: The data for training and testing with information about each loan application at Home Credit. Each loan has its row as feature SK_ID_CURR as an identifier or a unique key.

The TARGET of training application data has two values indicating 0: indicated the loan was repaid or 1: the loan was not repaid.

bureau: data from other financial organizations about the client's prior credit. Each previous credit has its own row in the bureau.

bureau_balance: monthly information about past credit history in the bureau. A previous credit can include numerous rows, one for each month of the credit period.

previous_application: Past loan applications made by customers with loans at Home Credit are included in the application data. The application data allows for many prior loans for each current loan. The feature SK ID PREV serves to distinguish each previous application, which contains one row.

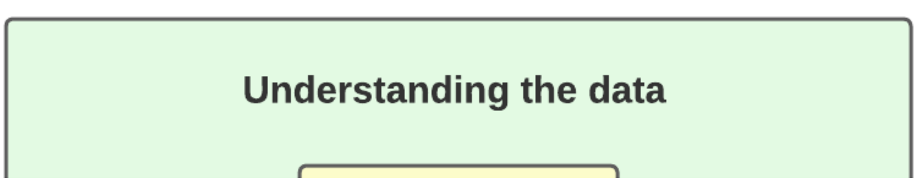
POS_CASH_BALANCE: monthly information on prior point-of-sale or cash loans that customers have taken out through Home Credit. A single previous loan can have numerous rows, each representing a month from a previous point of sale or cash loan.

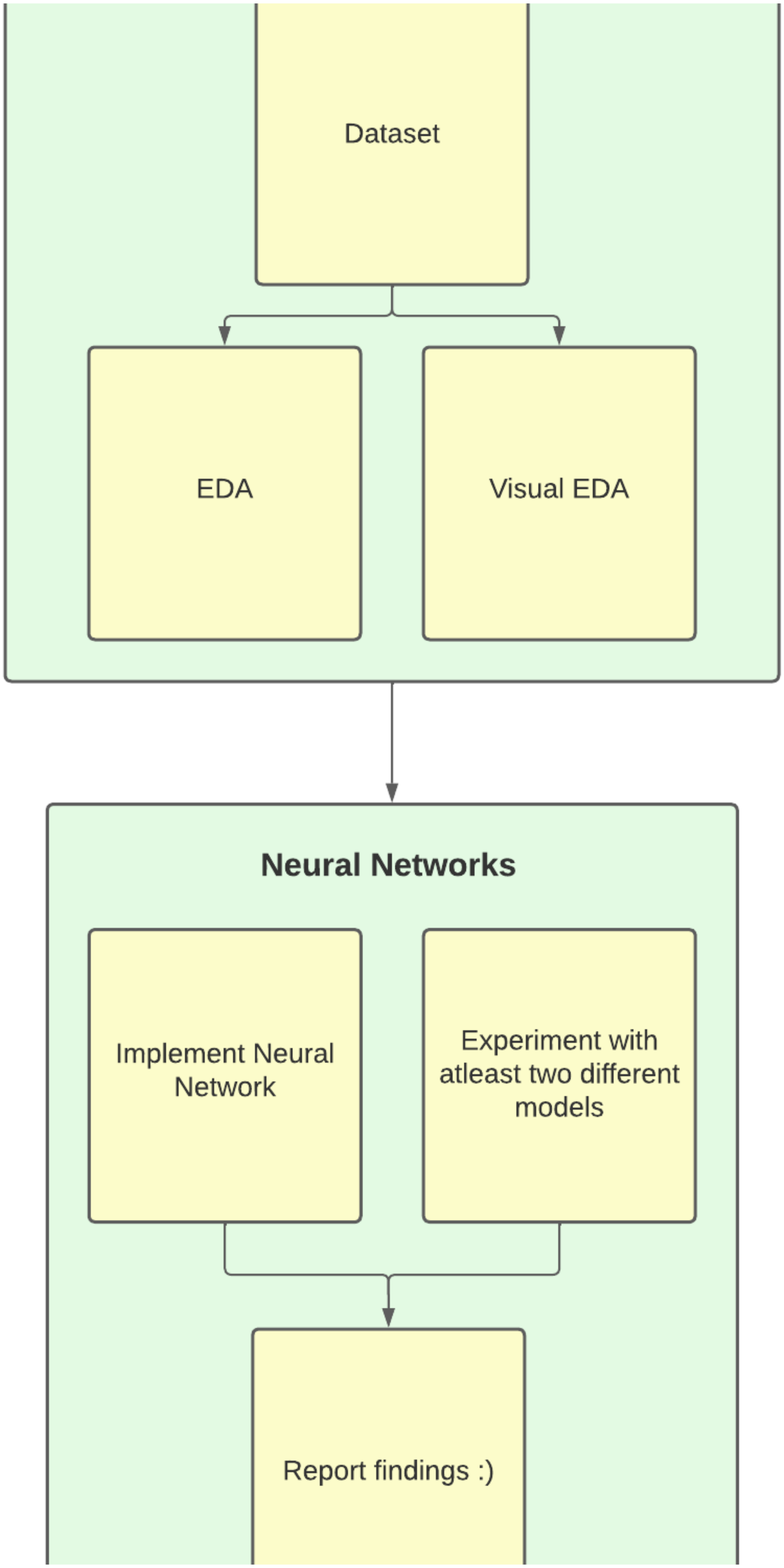
credit_card_balance: data about prior credit cards that Home Credit customers have had on a monthly basis. Every row represents a month's worth of credit card debt, and a single credit card may have several rows.

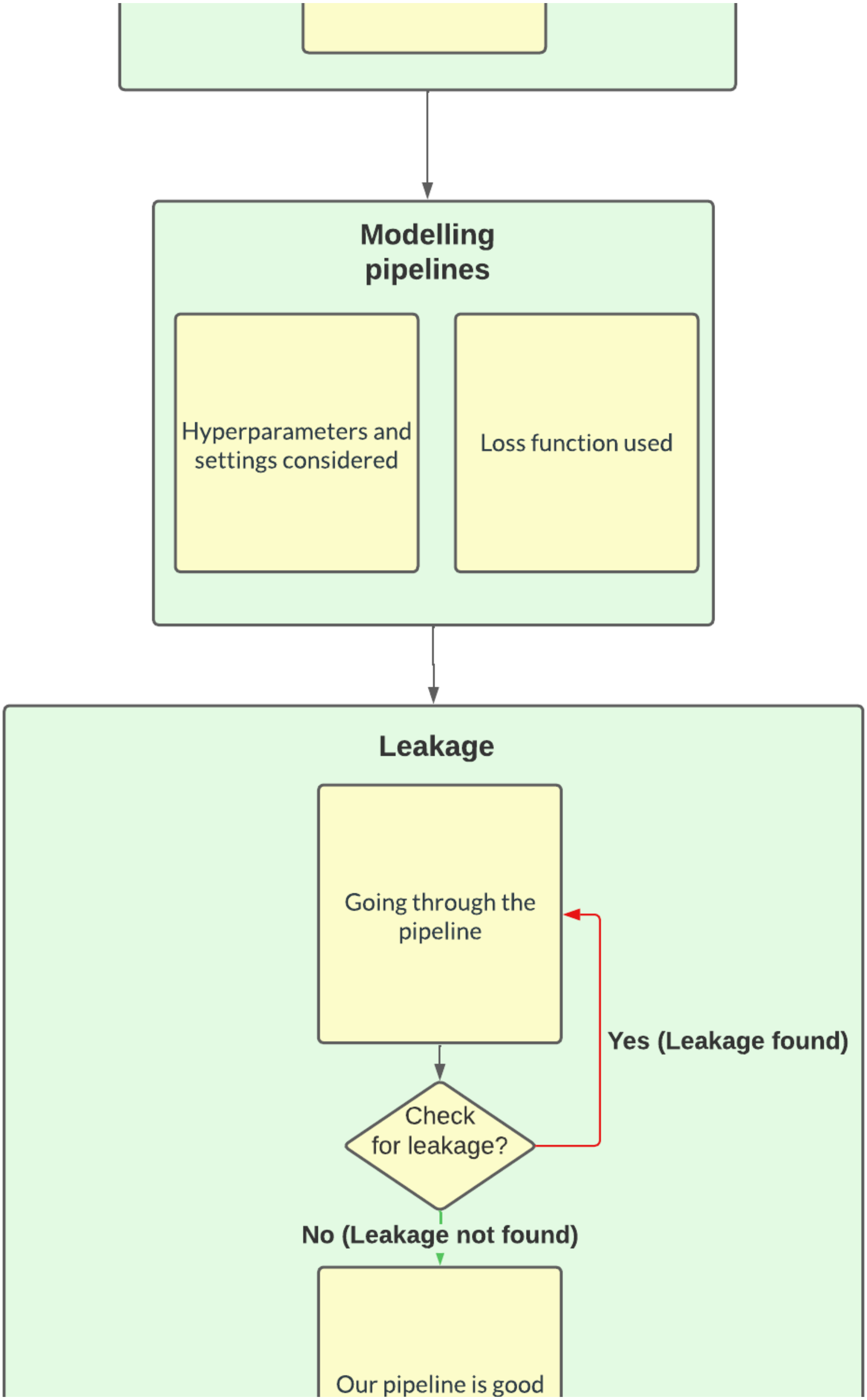
installments_payment : history of payments for prior loans with Home Credit. Every made payment has its own row, and every missed payment has its own row.

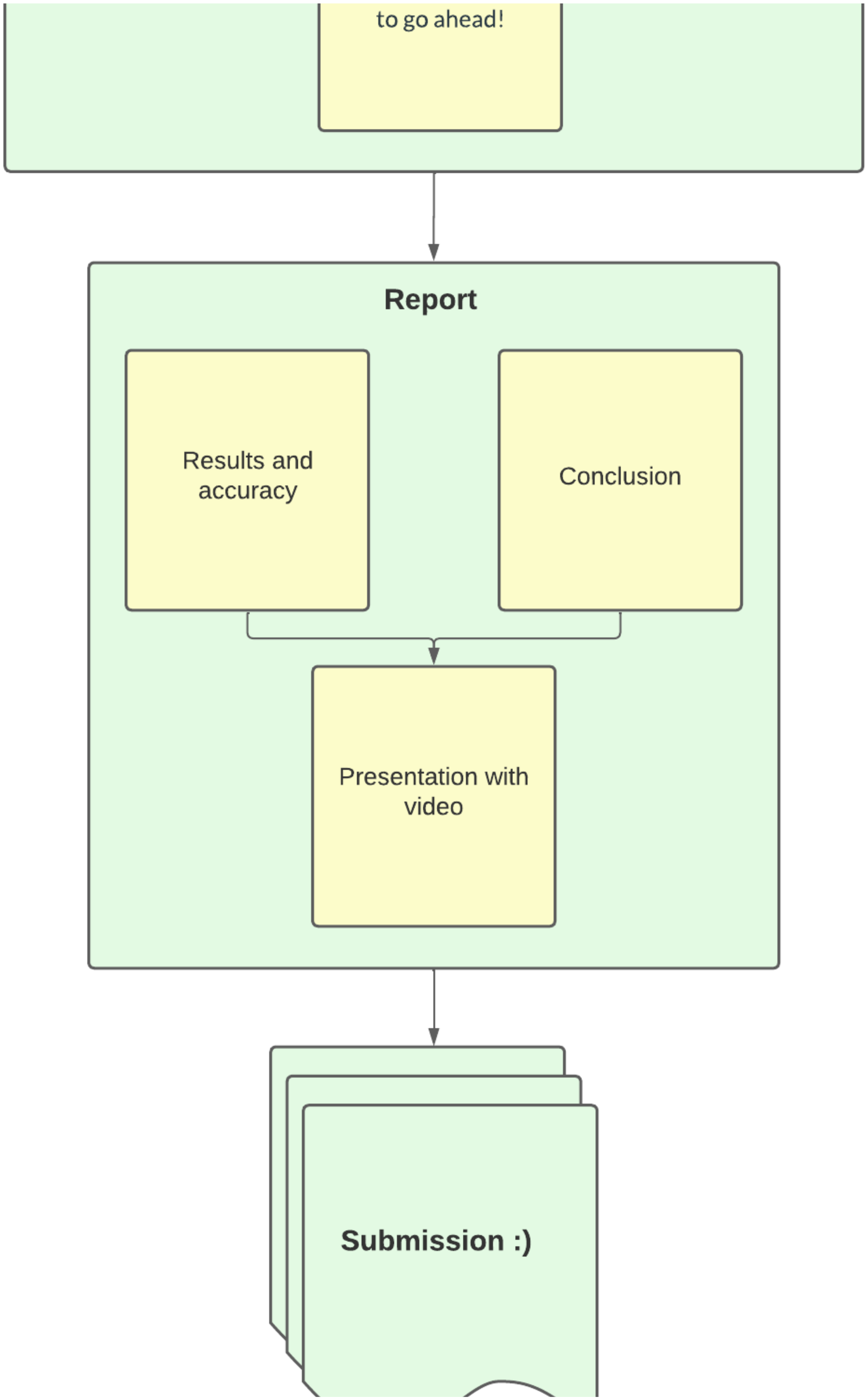
Tasks to be tackled:

1. Neural Network Implementation
2. Modeling Pipelines using Loss Functions
3. Checking for Leakage in the pipeline




Dataset
EDA
Visual EDA
Neural Networks
Implement Neural Network
Experiment with atleast two different models
Report findings :)


Modelling pipelines
Hyperparameters and settings considered
Loss function used
Leakage
Going through the pipeline
Yes (Leakage found)
Check for leakage?
No (Leakage not found)
Our pipeline is good


to go ahead!
Report
Results and accuracy
Conclusion
Presentation with video
Submission :)

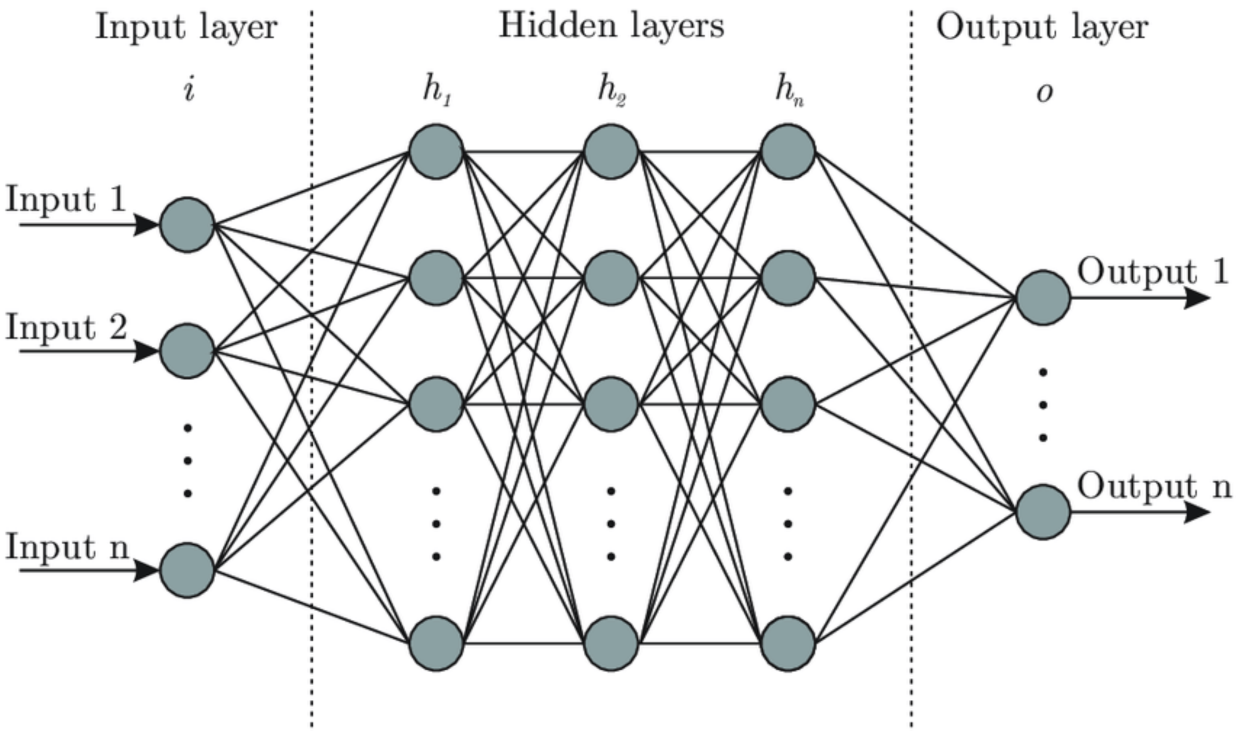
1. We make sure to use the given dataset as much as possible by tweaking it wherever necessary.
2. To tweak the data, we need to visualize the dataset and understand it. Therefore, we perform EDA.
3. Once we gather the required data, we plan to performed feature engineering in Phase 3 and selecting the essential attributes that contribute to the accuracy of the data and put it into the dataframe called final_features which is the dataset we will be used to train our model with.
4. We will be designing neural network architecture.We plan to perform experiment with atleast two different network architectures by playing around with activation functions and hidden layers and report the findings.
5. Later we plan to check for any leakage present in our pipeline
6. We record the results generated.

Neural Network

In [4]:
```
from IPython.display import Image


Image(url="https://miro.medium.com/max/1063/0*u-AnjlGU9IxM5_Ju.png",width =
```

Out[4]:



When we define a model, we define its layers. To be more specific, we use the forward() function to bypass the layers and propagate input. While there are numerous layers available, we exclusively use Linear, RELU, and Sigmoid only in our model.

- The activation functions RELU and Sigmoid layers. This is demonstrated in our execution above.
- We use stochastic gradient descent as an optimization algorithm while training the model.

We count the number of training epochs in a loop. Then, for mini-batches and stochastic gradient descent, we write an inner loop. Examine the Model We retrieved the numpy array and rounded the values to class values. Then we saved it. The final step is to compute accuracy. So we gathered the predictions for the test dataset, compared them to the predicted values of the test set, and finally calculated the performance metric.

We have designed two neural network models in total.

1st neural network architecture in string form:

161 – 55 – Relu – 15 – Relu – 5 – Relu – 1 – Sigmoid.

1) 1st Neural Network:

```
Hidden layers used: 3

Activation functions used: ReLU and Sigmoid

Epochs: 40

Optimizer selected: SGD

Learning rate: 0.0001
```

2nd neural network architecture in string form:

161 – 25 – Relu – 12 – Relu – 1 – Sigmoid.

2) 2nd Neural Network:

```
Hidden layers used: 2

Activation functions used: ReLU and Sigmoid

Epochs: 28

Optimizer selected: SGD

Learning rate: 0.0011
```

Leakage

Data leaking occurs when the model is created using data that is not part of the training dataset. Data leakage frequently results in unrealistically high levels of performance on the test set since the model is being run on data that it has already seen. To ensure that there is no data leakage, we run the model multiple times. Through multiple runs, we consistently came to the same conclusions, and the accuracy has not significantly improved. To ensure that the outcomes were consistent, we also ran the model independently numerous times on test and validation data. In addition, we did not see any improvement in accuracy throughout the course of those several runs. Additionally, we checked for any duplication.

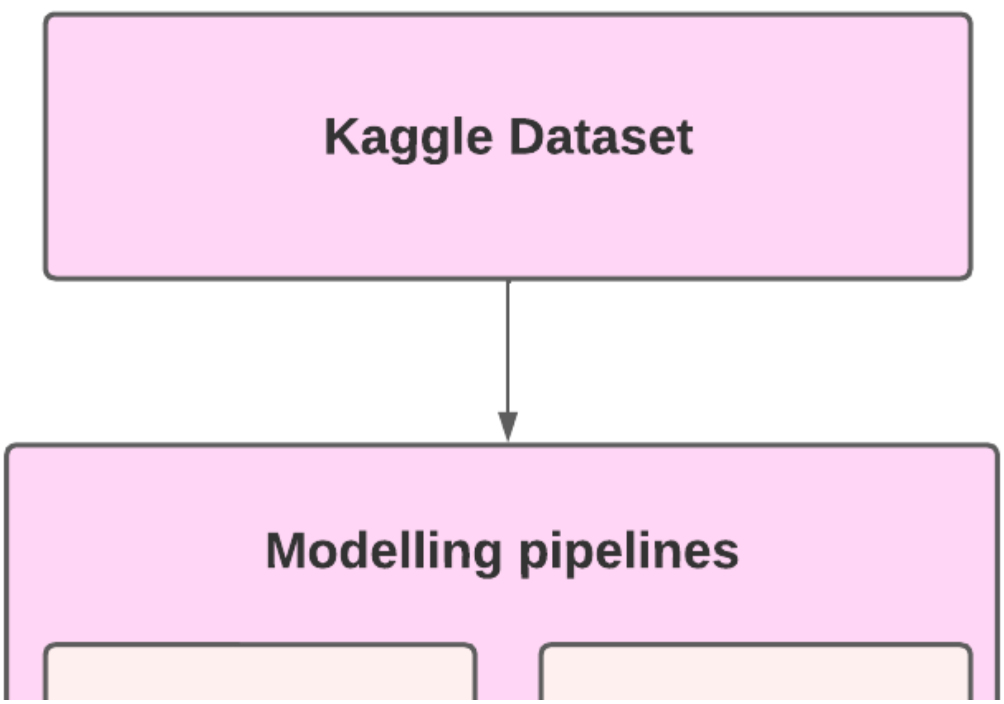
Cardinal Sins of ML

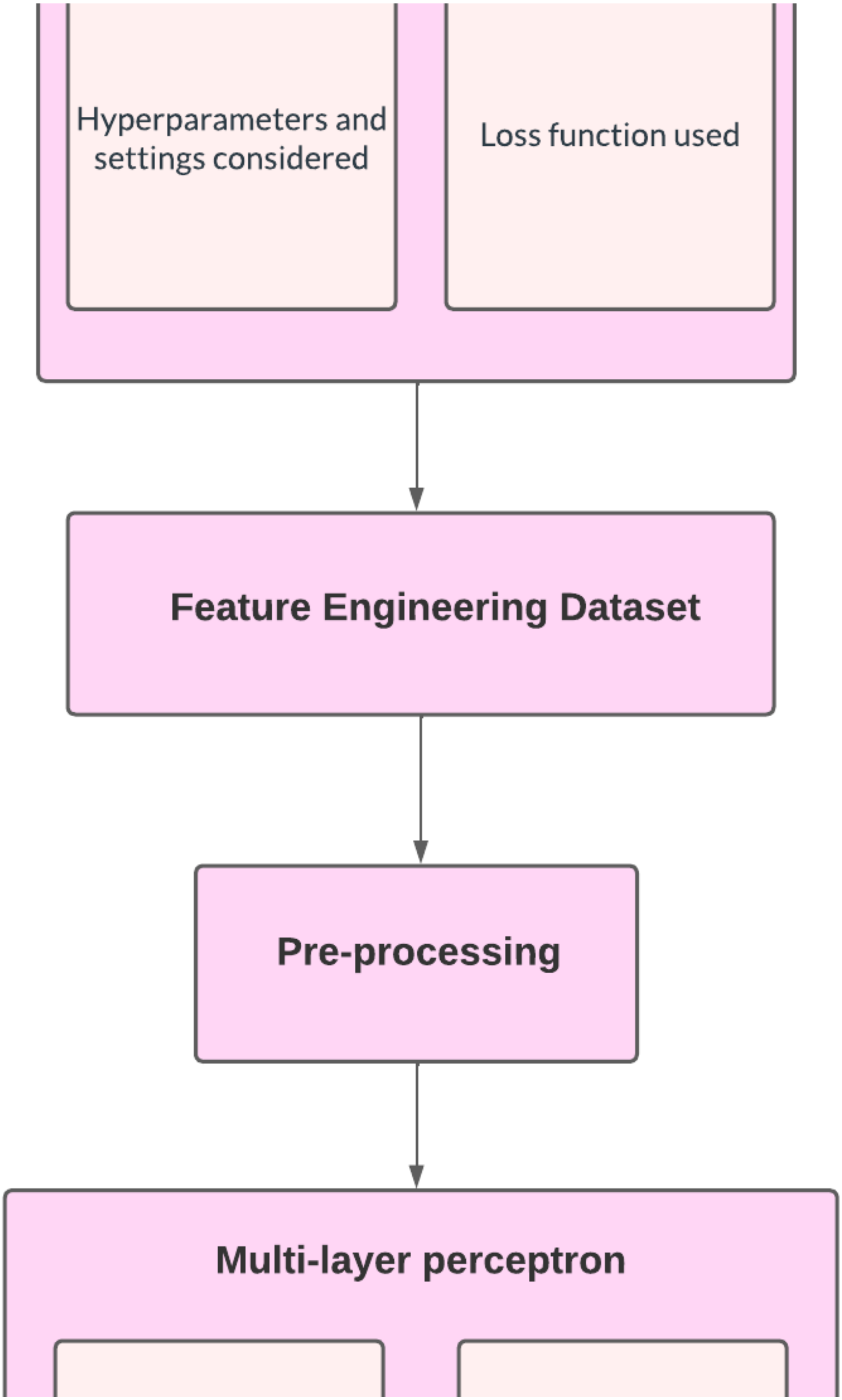
As the application_train and application_test datasets were provided to us seperately. We did not make a rookie mistake of abusing the data and model.

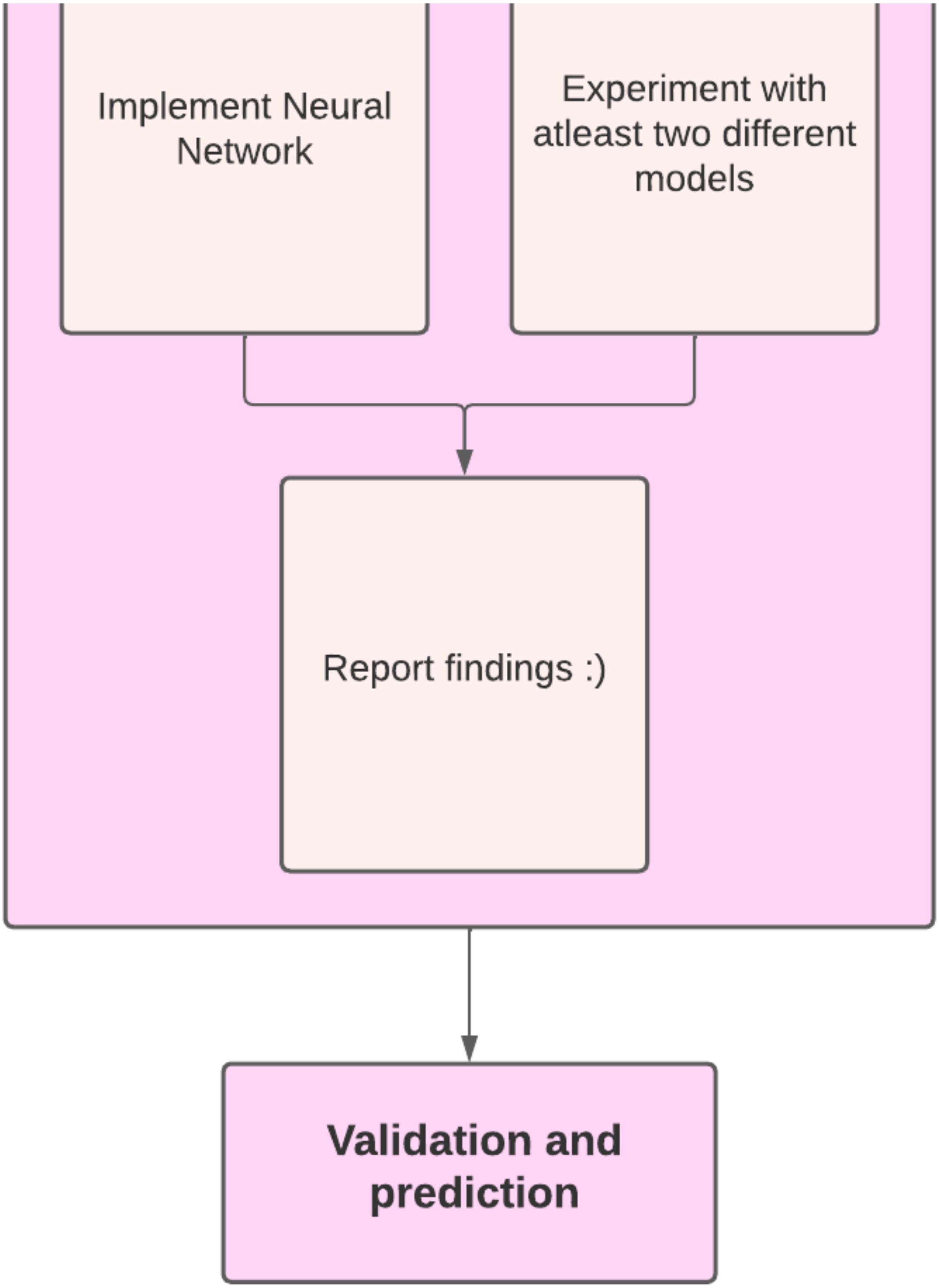
Further we have not performed any cross fold validation on the application_train dataset after splitting it so we have refrained from exposing test dataset to be part of training.

In [ ]:

Model Pipeline




Hyperparameters and settings considered
Loss function used
Feature Engineering Dataset
Pre-processing
Multi-layer perceptron


Implement Neural Network
Experiment with atleast two different models
Report findings :)
Validation and prediction

During the previous phase of our project, we examined the data, made an effort to clean and preprocess it, and then started modeling the project using machine learning techniques. As a starting point, we trained our model using logistic regression and Random Forest. Finally, we evaluated how well our models performed in comparison to the baseline models.

As our problem involves both categorical and numerical variables, and as a final step, we need to forecast the target variable in categorical value itself, i.e. whether the client is creditworthy or not, logistic regression is one of the approaches that we have assumed to provide us the solution. To reach this conclusion, we used a variety of predictors.

We measured our baseline model using LogLoss, AOC/ROC, and validation accuracy.

Results and Discussions

Summarizing all the results

Interpretation of Phase 2 Results

[55...

	PIPELINE	DATASET	Acc_Train	Acc_Val	Acc_Test	Time-Train	Time-Test	AUC-ROC	Description
0	LogisticRegression as Baseline	HCDR	91.9438%	91.8207%	91.9451%	5.3347	0.4631	74.2923%	LogisticRegresssion pipeline with Numerical an...
1	RandomForest as Baseline	HCDR	91.9425%	91.9646%	91.9646%	6.1800	0.6700	72.9297%	RandomForest pipeline with Numerical and Categ...

Interpretation of Phase 3 Results

In [228]:

```
auc_xg = roc_auc_score(y_test, xgboost_search.predict_proba(X_test)[:, 1])
try: experimentLog

except : experimentLog = pd.DataFrame(columns=["PIPELINE", "DATASET", "Acc_Train", "Acc_Val", "Acc_Test",
"Time-Train", "Time-Test", "AUC-ROC", "Description",])
experimentLog.loc[len(experimentLog)] =[f"Gridsearch Xgboost with {input_nums} inputs", "HCDR", f"{hlpr(AC_TRAIN)}%"
                                        f"{hlpr(AC_TEST)}%", train_time, test_time, f"{hlpr(auc_xg)}%",
                                         "Xgboost GridSearch with selected features"]

experimentLog
```

Out[228]:

	PIPELINE	DATASET	Acc_Train	Acc_Val	Acc_Test	Time-Train	Time-Test	AUC-ROC	Description
0	best params LogReg	HCDR	92.2875%	92.2861%	92.2861%	1.0031	0.0389	73.5931%	Baseline 1 LogReg pipeline with Cat+Num features
1	GridSearchCV LogReg without weights balanced	HCDR	92.2875%	92.2861%	92.2861%	1.0031	0.0389	73.5931%	GridSearchCV Logistic regression pipeline with...
2	GridSearchCV RandomForestClassifier	HCDR	100.0%	92.3188%	92.3188%	1.0031	0.1003	69.1445%	GridSearchCV RandomForestClassifier pipeline w...
3	GridSearchCV RandomForestClassifier	HCDR	100.0%	92.3188%	92.3188%	1.0031	0.1003	69.0858%	bestparams RandomForestClassifier pipeline wit...
4	Gridsearch Xgboost with 80 inputs	HCDR	77.7141%	74.1457%	74.1457%	1029.8041	0.0568	74.1457%	Xgboost GridSearch with selected features

Interpretation of Phase 4 Results

Out[33]:

	Dataset	Learning rate	Epochs	No_Hidden_layers	Accuracy_score	AUC-ROC	Description
0	HCDR	0.0001	40	4	0.919036	0.742876	Multi layer perceptron exp 1
1	HCDR	0.0011	28	3	0.920033	0.742862	Multi layer perceptron exp 2

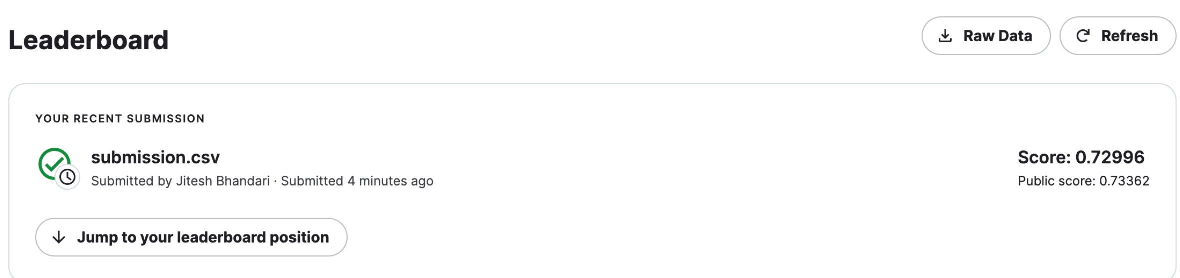
The major aim of the project was to determine if the client is creditworthy or not. In phase 1 of our project we trained the model using logistic regression and random forest regressor without performing any feature engineering or modifications on the dataset and obtain the accuracy of 91.94% on the dataset, later in the next phase after performing hyperparameter tuning and feature engineering to generate a new dataframe after combining multiple tables the model was able to predict with an accuracy of 92.2% and finally in this phase of the project we chose to utilize the dataset from the feature engineered dataframe exported to csv as final_features, we preprocessed this dataset before using it in our multilayer perceptron,later 75% of the data from this table was used for training the neural network model to obtain the accuracies as stated above for different networking models.

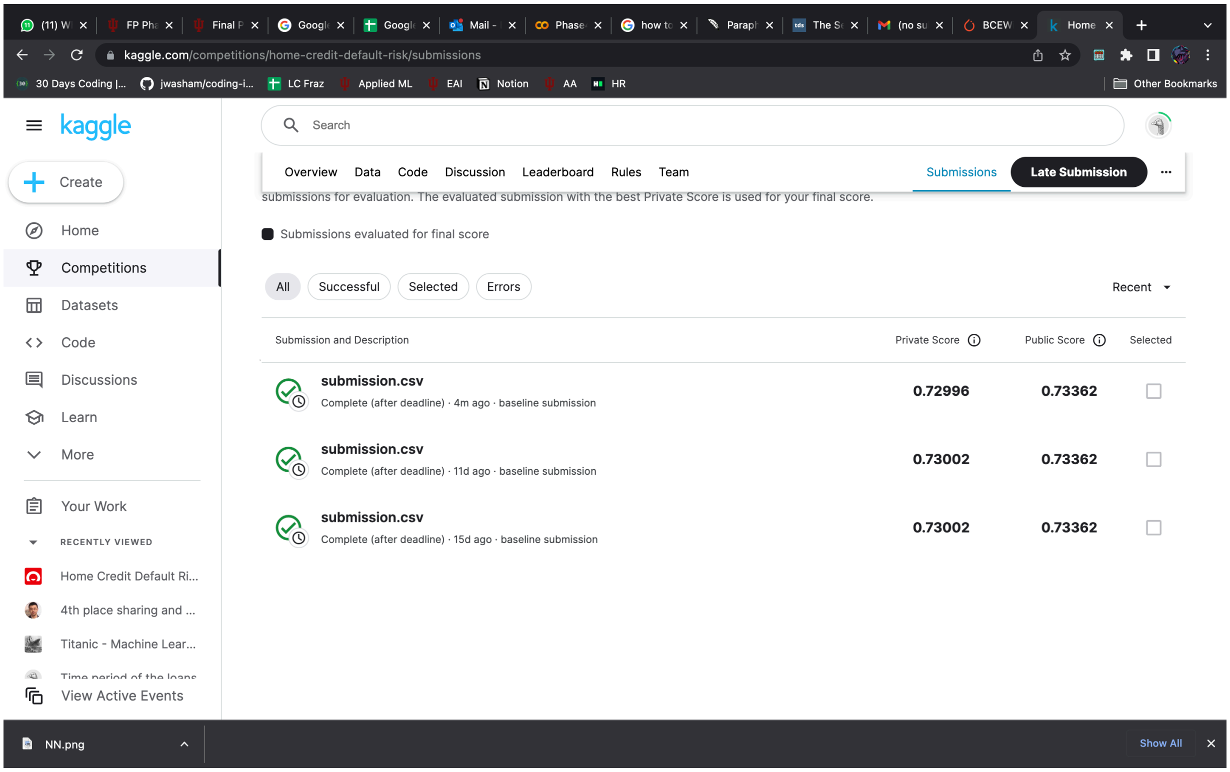
Conclusion

The HCDR project's goal is to forecast the repayment capacity of the affected population. This is a significant project because both the lender and the borrower require well-established projections. Because the data includes people's lives, HomeCredit will require the highest level of precision to ensure that it is forecasted accurately.

We did Exploratory Data Analysis in phase one, where we discovered several insights into the data and learned a lot about how to extract significant information from it. Following that, we built a baseline model with pipelines and Logistic Regression, learning how to build models, train them, and test them using various metrics. In Phase 3, we finished feature engineering and learned how to design significant features to improve the model. Then we used GridSearchCV to perform Hyperparameter tuning, which taught us how to improve accuracy by combining multiple models. In Phase 4, we created an MLP model and tested it with AUC ROC score, but we did not get the anticipated AUC ROC score by training the dataset with the neural network by the comparison made from the kaggle submissions we can see our neural networks AUC ROC score is slightly less than Logistic Regression AUC ROC score.

Kaggle Submission




kaggle.com/competitions/home-credit-default-risk/submissions
30 Days Coding |...
jwasham/coding-i...
LC Fraz
Applied ML
EAI
Notion
AA
HR
Other Bookmarks
kaggle
Search
Create
Home
Competitions
Datasets
Code
Discussions
Learn
More
Your Work
RECENTLY VIEWED
Home Credit Default Ri...
4th place sharing and ...
Titanic - Machine Lear...
View Active Events
Overview
Data
Code
Discussion
Leaderboard
Rules
Team
Submissions
Late Submission
submissions for evaluation. The evaluated submission with the best Private Score is used for your final score.
Submissions evaluated for final score
All
Successful
Selected
Errors
Recent
Submission and Description
Private Score
Public Score
Selected
submission.csv
Complete (after deadline) · 4m ago · baseline submission
0.72996
0.73362
submission.csv
Complete (after deadline) · 11d ago · baseline submission
0.73002
0.73362
submission.csv
Complete (after deadline) · 15d ago · baseline submission
0.73002
0.73362
NN.png
Show All

In [ ]: