Marketing campaign optimisation

Dataset

In [1]:
```
import pandas as pd
import numpy as np

data = pd.read_csv('../Data/store.csv', index_col=0)
data.head()
```

Out[1]:

	REC	FRE	MON	CC_CARD	AVRG	PSWEATERS	PKNIT_TOPS	PKNIT_DRES
CUSTOMER								
1	208	2	368.46	0	184.23	0.18	0.00	0.00
2	6	4	258.00	1	64.50	0.26	0.16	0.00
3	327	2	77.00	0	38.50	1.00	0.00	0.00
4	66	8	846.06	1	105.75	0.38	0.00	0.05
5	49	1	87.44	0	87.44	0.20	0.20	0.00

5 rows × 47 columns

In [2]:
```
from sklearn.model_selection import train_test_split

SID = 470403778
index_train, index_test  = train_test_split(np.array(data.index), train_si:
train = data.loc[index_train,:].copy()
test =  data.loc[index_test,:].copy()
```

1. Exploratory Data Analysis

Starting with some exploratory data analysis, we examine how many customers responsed to the marketing campaign against how many did not respond. This is done in the training and test sets.

Finding missing values

In [3]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
NaN_values = train.isnull().sum().sort_values(ascending=False)
```

Dummy encode categorical variables

In [5]:
```
test = pd.get_dummies(test, columns=['VALPHON'], drop_first=True)
```

In [6]:
```
train = pd.get_dummies(train, columns=['VALPHON'], drop_first=True)
```

Creating a validation set

In [7]:
```
# Splitting the train to create a validation set
# Separating the predictors
target_y = train['RESP']
features_x = train.loc[:, train.columns != 'RESP']
X_train, X_val, y_train, y_val = train_test_split(features_x, target_y, te
print(f"The number of examples for the train set is {X_train.shape[0]}")
print(f"The number of examples for the validation set is {X_val.shape[0]}"
```

```
The number of examples for the train set is 10435
The number of examples for the validation set is 2609
```

Outlier detection

In [8]:
```
from sklearn.neighbors import LocalOutlierFactor

# fit the model for outlier detection (default)
clf = LocalOutlierFactor(n_neighbors=20, contamination=0.1)
y_pred = clf.fit_predict(X_train)
# n_errors = (y_pred != ground_truth) #.sum()
X_scores = clf.negative_outlier_factor_
```

In [9]:
```
NaN_values = train.isnull().sum().sort_values(ascending=False)
```

There are no missing values in the train or test sets.

Linear Correlations

Examining correlations for important variables.

In [10]:
```
abs(train.corr()['RESP']).sort_values(ascending=False)
```

Out[10]:
```
RESP            1.000000
FRE             0.402507
CLASSES         0.378530
STYLES          0.358711
RESPONDED       0.346897
RESPONSERATE    0.331282
MON             0.321560
SMONSPEND       0.315077
LTFREDAY        0.308066
STORES          0.307376
COUPONS         0.305152
TMONSPEND       0.275470
REC             0.267181
CC_CARD         0.243565
CCSPEND         0.237677
HI              0.235219
FREDAYS         0.228569
PROMOS          0.228448
OMONSPEND       0.219625
PSSPEND         0.207955
MAILED          0.207122
DAYS            0.184701
PREVPD          0.173793
WEB             0.169937
AXSPEND         0.117901
VALPHON_Y       0.111959
MARKDOWN        0.100214
PERCRET         0.071388
GMP             0.057840
AVRG            0.054603
AMSPEND         0.049543
PCOLLSPND       0.043548
PSUITS          0.038827
PSWEATERS       0.028312
PDRESSES        0.025349
POUTERWEAR      0.021436
PBLOUSES        0.016845
PJACKETS        0.015273
PCAR_PNTS       0.014532
PFASHION        0.012408
PCAS_PNTS       0.011914
CLUSTYPE        0.008818
PKNIT_DRES      0.008799
PSHIRTS         0.008607
PKNIT_TOPS      0.002406
PJEWELRY        0.001980
PLEGWEAR        0.001913
Name: RESP, dtype: float64
```

Dabl to detect data types, could investigate the data types more

Let's use dabl to detect which features may be useless.

In [11]:
```python
from dabl import detect_types
train_types = detect_types(train)
test_types = detect_types (test)
```

In [12]:
```
train_types
```

Out[12]:

	continuous	dirty_float	low_card_int	categorical	date	free_string	usele
REC	True	False	False	False	False	False	Fal
FRE	False	False	True	False	False	False	Fal
MON	True	False	False	False	False	False	Fal
CC_CARD	False	False	False	True	False	False	Fal
AVRG	True	False	False	False	False	False	Fal
PSWEATERS	True	False	False	False	False	False	Fal
PKNIT_TOPS	True	False	False	False	False	False	Fal
PKNIT_DRES	True	False	False	False	False	False	Fal
PBLOUSES	True	False	False	False	False	False	Fal
PJACKETS	True	False	False	False	False	False	Fal
PCAR_PNTS	True	False	False	False	False	False	Fal
PCAS_PNTS	True	False	False	False	False	False	Fal
PSHIRTS	True	False	False	False	False	False	Fal
PDRESSES	True	False	False	False	False	False	Fal
PSUITS	True	False	False	False	False	False	Fal
POUTERWEAR	True	False	False	False	False	False	Fal
PJEWELRY	True	False	False	False	False	False	Fal
PFASHION	True	False	False	False	False	False	Fal
PLEGWEAR	True	False	False	False	False	False	Fal
PCOLLSPND	True	False	False	False	False	False	Fal
AMSPEND	False	False	False	False	False	False	Tr
PSSPEND	True	False	False	False	False	False	Fal
CCSPEND	True	False	False	False	False	False	Fal
AXSPEND	True	False	False	False	False	False	Fal
TMONSPEND	True	False	False	False	False	False	Fal
OMONSPEND	True	False	False	False	False	False	Fal
SMONSPEND	True	False	False	False	False	False	Fal
PREVPD	True	False	False	False	False	False	Fal
GMP	True	False	False	False	False	False	Fal
PROMOS	False	False	True	False	False	False	Fal
DAYS	True	False	False	False	False	False	Fal

FREDAYS	True	False	False	False	False	False	Fal
MARKDOWN	True	False	False	False	False	False	Fal
CLASSES	False	False	True	False	False	False	Fal
COUPONS	False	False	True	False	False	False	Fal
STYLES	True	False	False	False	False	False	Fal
STORES	False	False	True	False	False	False	Fal
WEB	False	False	False	False	False	False	Tr
MAILED	False	False	True	False	False	False	Fal
RESPONDED	False	False	True	False	False	False	Fal
RESPONSERATE	True	False	False	False	False	False	Fal
HI	True	False	False	False	False	False	Fal
LTFREDAY	True	False	False	False	False	False	Fal
CLUSTYPE	False	False	True	False	False	False	Fal
PERCRET	True	False	False	False	False	False	Fal
RESP	False	False	False	True	False	False	Fal
VALPHON_Y	False	False	False	True	False	False	Fal

Dabl flags AMSPEND and WEB as being useless in the train, but only WEB as being a useless feature in the test. Let's investigate why.

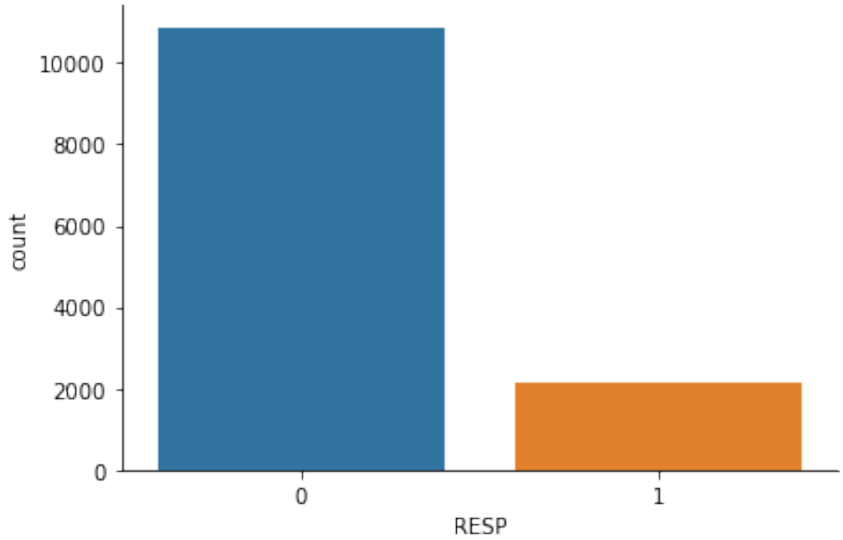
In [13]:
```
train['WEB'].value_counts()
```

Out[13]:
```
0    12501
1      543
Name: WEB, dtype: int64
```

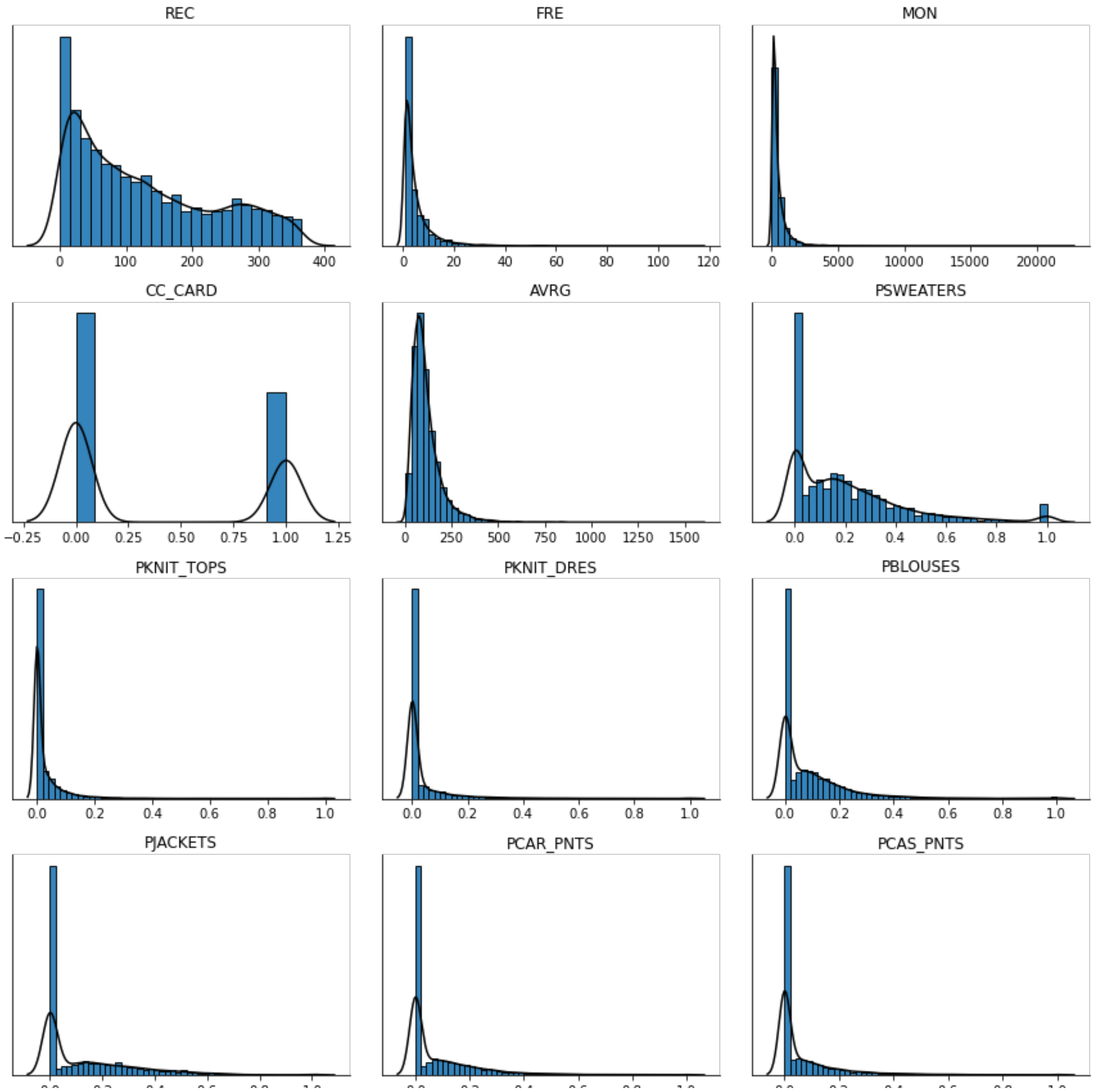
Dabl flags WEB as a useless predictor as shopping predominantly occurs on-site.

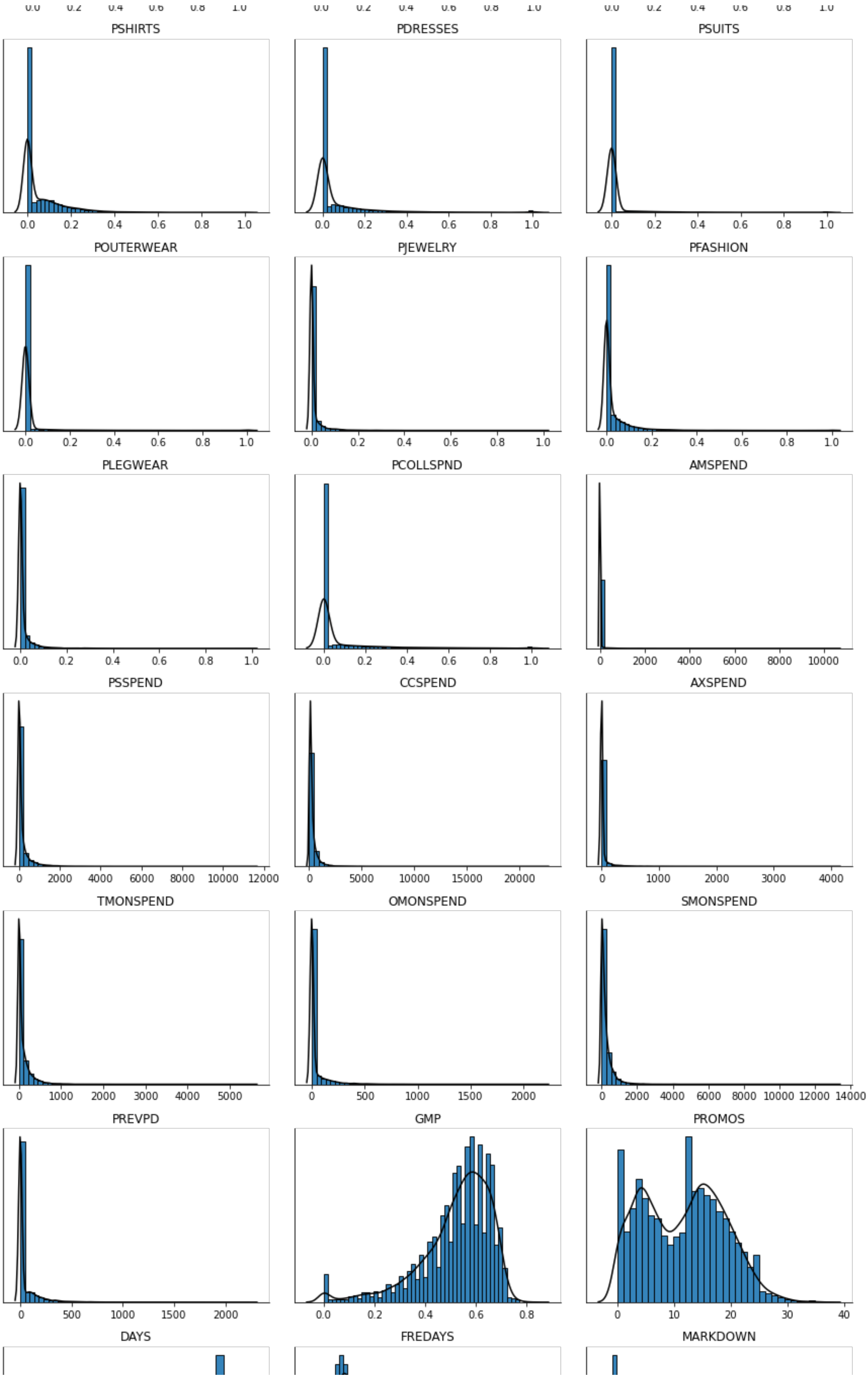
Response countplot

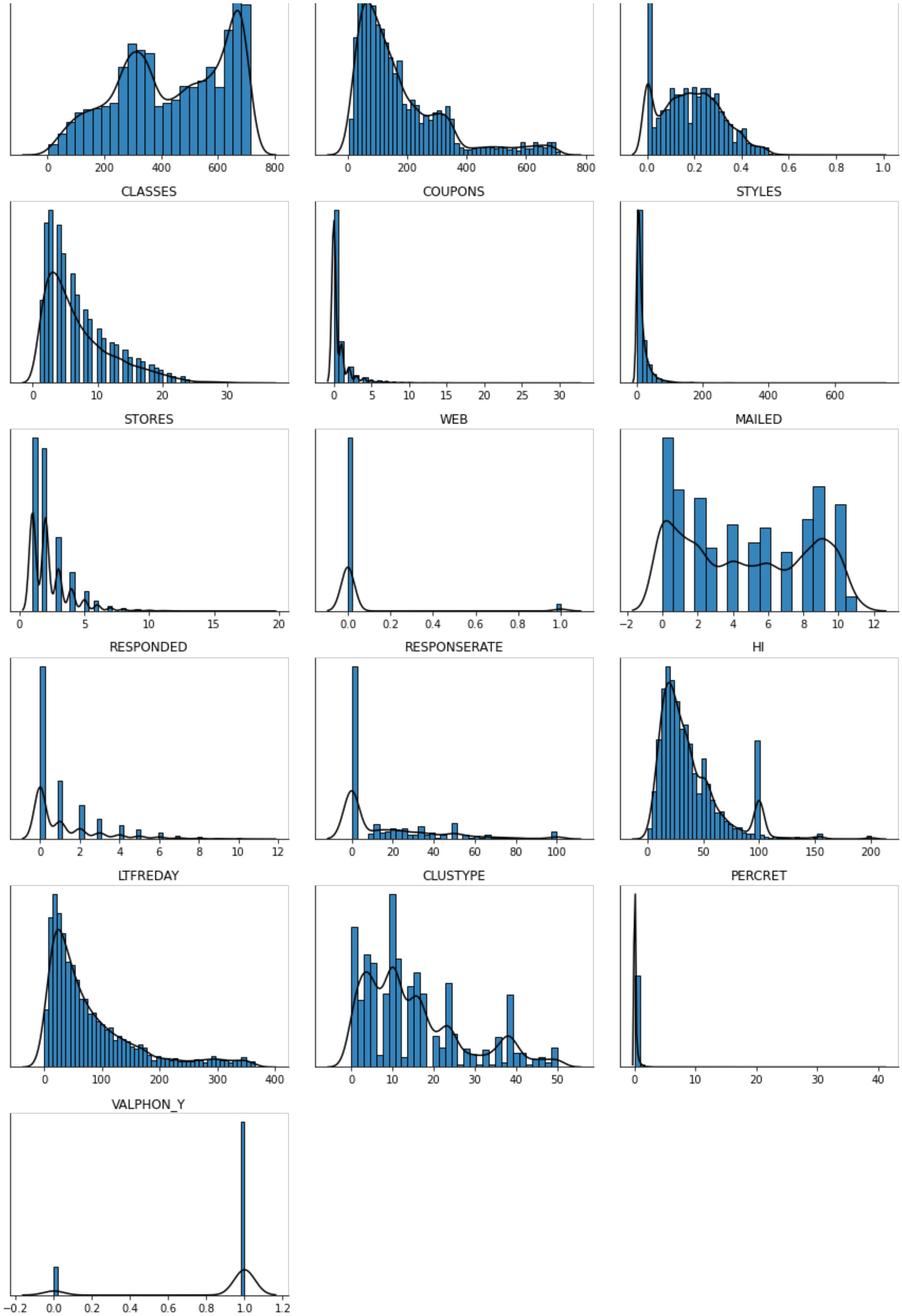
In [14]:
```
import seaborn as sns
sns.countplot(train['RESP'].astype(object))
sns.despine()
```



In [15]:
```
from statlearning import plot_dists
fig, ax = plot_dists(X_train)
```



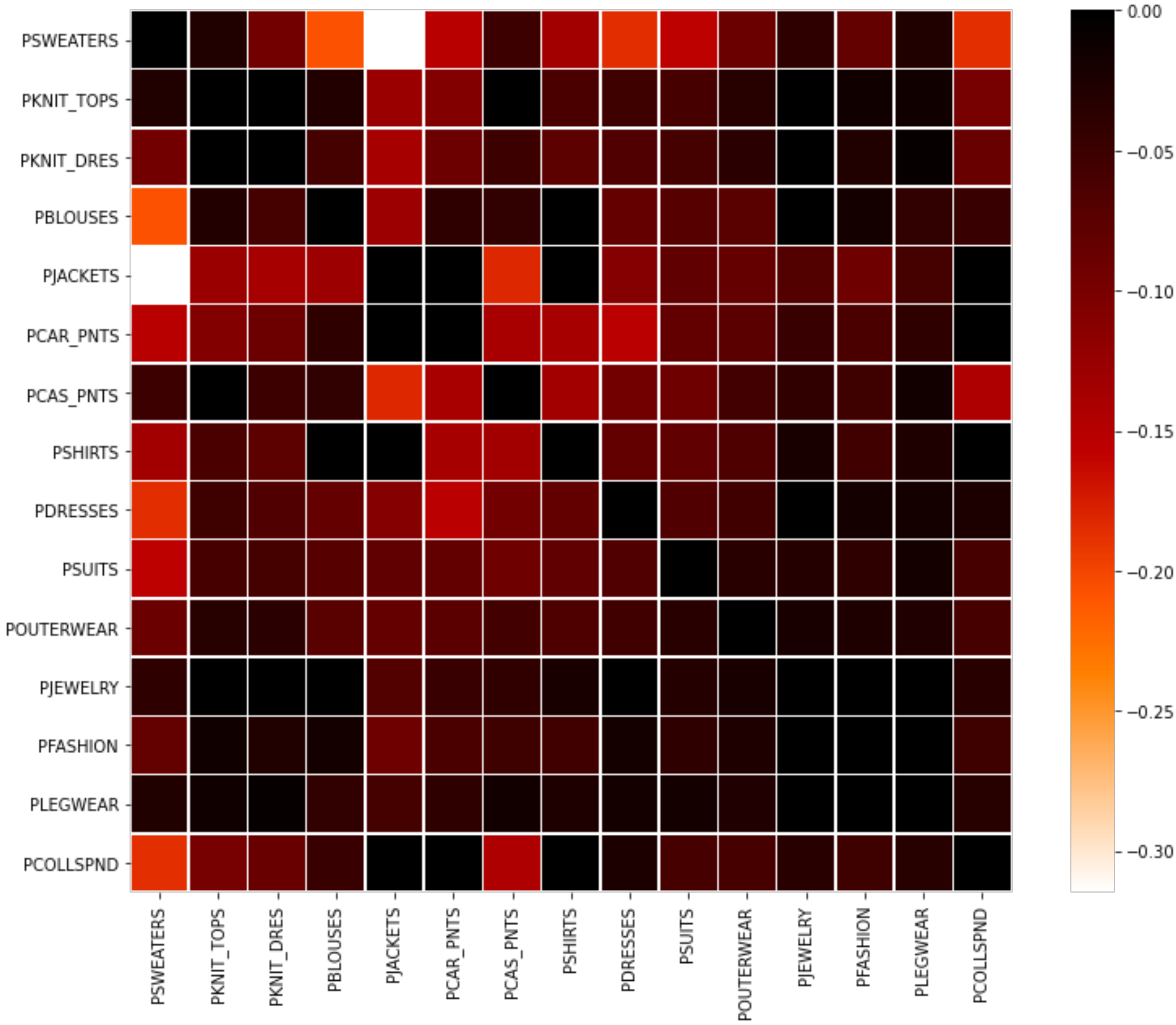

PSHIRTS
0.0 0.2 0.4 0.6 0.8 1.0
PDRESSES
0.0 0.2 0.4 0.6 0.8 1.0
PSUITS
0.0 0.2 0.4 0.6 0.8 1.0
POUTERWEAR
0.0 0.2 0.4 0.6 0.8 1.0
PJEWELRY
0.0 0.2 0.4 0.6 0.8 1.0
PFASHION
0.0 0.2 0.4 0.6 0.8 1.0
PLEGWEAR
0.0 0.2 0.4 0.6 0.8 1.0
PCOLLSPND
0.0 0.2 0.4 0.6 0.8 1.0
AMSPEND
0 2000 4000 6000 8000 10000
PSSPEND
0 2000 4000 6000 8000 10000 12000
CCSPEND
0 5000 10000 15000 20000
AXSPEND
0 1000 2000 3000 4000
TMONSPEND
0 1000 2000 3000 4000 5000
OMONSPEND
0 500 1000 1500 2000
SMONSPEND
0 2000 4000 6000 8000 10000 12000 14000
PREVPD
0 500 1000 1500 2000
GMP
0.0 0.2 0.4 0.6 0.8
PROMOS
0 10 20 30 40
DAYS
FREDAYS
MARKDOWN



Heatmap for the fraction spent on product category.

In [16]:
```
import matplotlib.pyplot as plt
f, ax = plt.subplots(figsize=(13,10))
sns.heatmap(train[['PSWEATERS','PKNIT_TOPS','PKNIT_DRES','PBLOUSES','PJACKI
```

Out[16]: <AxesSubplot:>



2. Feature Engineering

Outlier dummy variables

In [17]:
```
# Due to the offset threshold of -1.5
X_train['outlierdummy'] = np.where(X_scores<-1.5,1,0)

# To populate these columns
X_val['outlierdummy'] = 0
test['outlierdummy'] = 0
```

Interaction effects according to the heatmap

In [18]:
```
# Train
X_train['PKNIT_TOPSXPKNIT_DRES'] = X_train['PKNIT_TOPS']*X_train['PKNIT_DRI
X_train['PJACKETSXPCAR_PNTS'] = X_train['PJACKETS']*X_train['PCAR_PNTS']
X_train['PJEWELRYXPFASHIONXPLEGWEAR'] = X_train['PJEWELRY']*X_train['PFASHI

# Validation and test (should I fill these with 0 or as in train?)
X_val['PKNIT_TOPSXPKNIT_DRES'] = X_val['PKNIT_TOPS']*X_val['PKNIT_DRES']
X_val['PJACKETSXPCAR_PNTS'] = X_val['PJACKETS']*X_val['PCAR_PNTS']
X_val['PJEWELRYXPFASHIONXPLEGWEAR'] = X_val['PJEWELRY']*X_val['PFASHION']*X

test['PKNIT_TOPSXPKNIT_DRES'] = test['PKNIT_TOPS']*test['PKNIT_DRES']
test['PJACKETSXPCAR_PNTS'] = test['PJACKETS']*test['PCAR_PNTS']
test['PJEWELRYXPFASHIONXPLEGWEAR'] = test['PJEWELRY']*test['PFASHION']*test
```

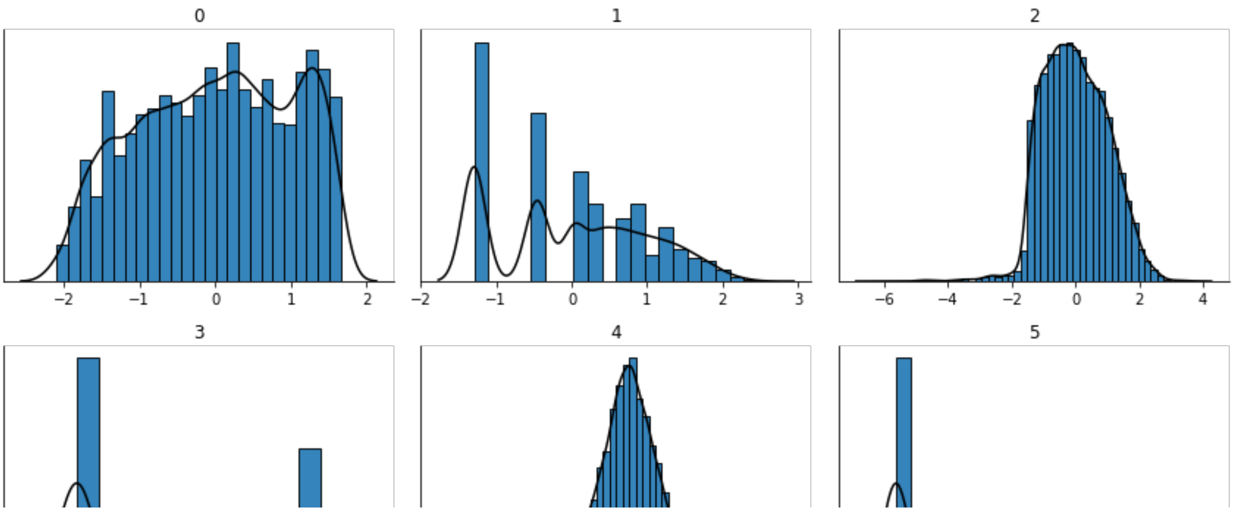
Yeo-Johnson Transformation on Predictors

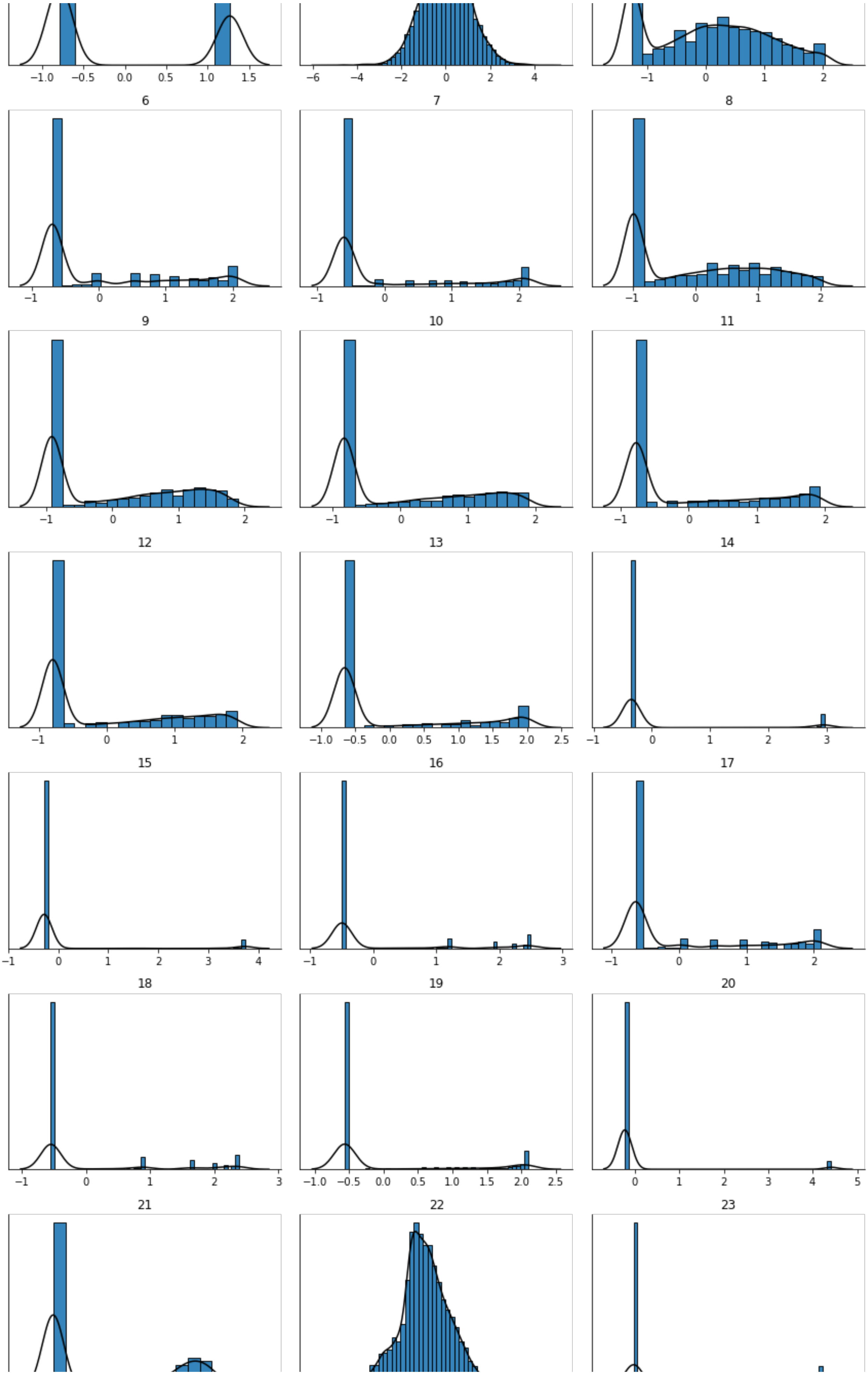
Since quite a few of the predictors are right-skewed, applying a Yeo-Johnson transformation should help correct for this non-normality.

In [19]:
```
from sklearn.preprocessing import PowerTransformer

# Yeo-Johnson
yj = PowerTransformer(method='yeo-johnson') # YJ is the default, this func
X_train = yj.fit_transform(X_train)
X_val = yj.transform(X_val)
X_train = pd.DataFrame(X_train)
X_val = pd.DataFrame(X_val)

y_test = test['RESP']
features_x = test.loc[:, test.columns != 'RESP']
X_test = yj.fit_transform(features_x)
X_test = pd.DataFrame(X_test)
```

Checking for change in distribution of predictors

In [20]:
```
fig, ax = plot_dists(X_train)
```

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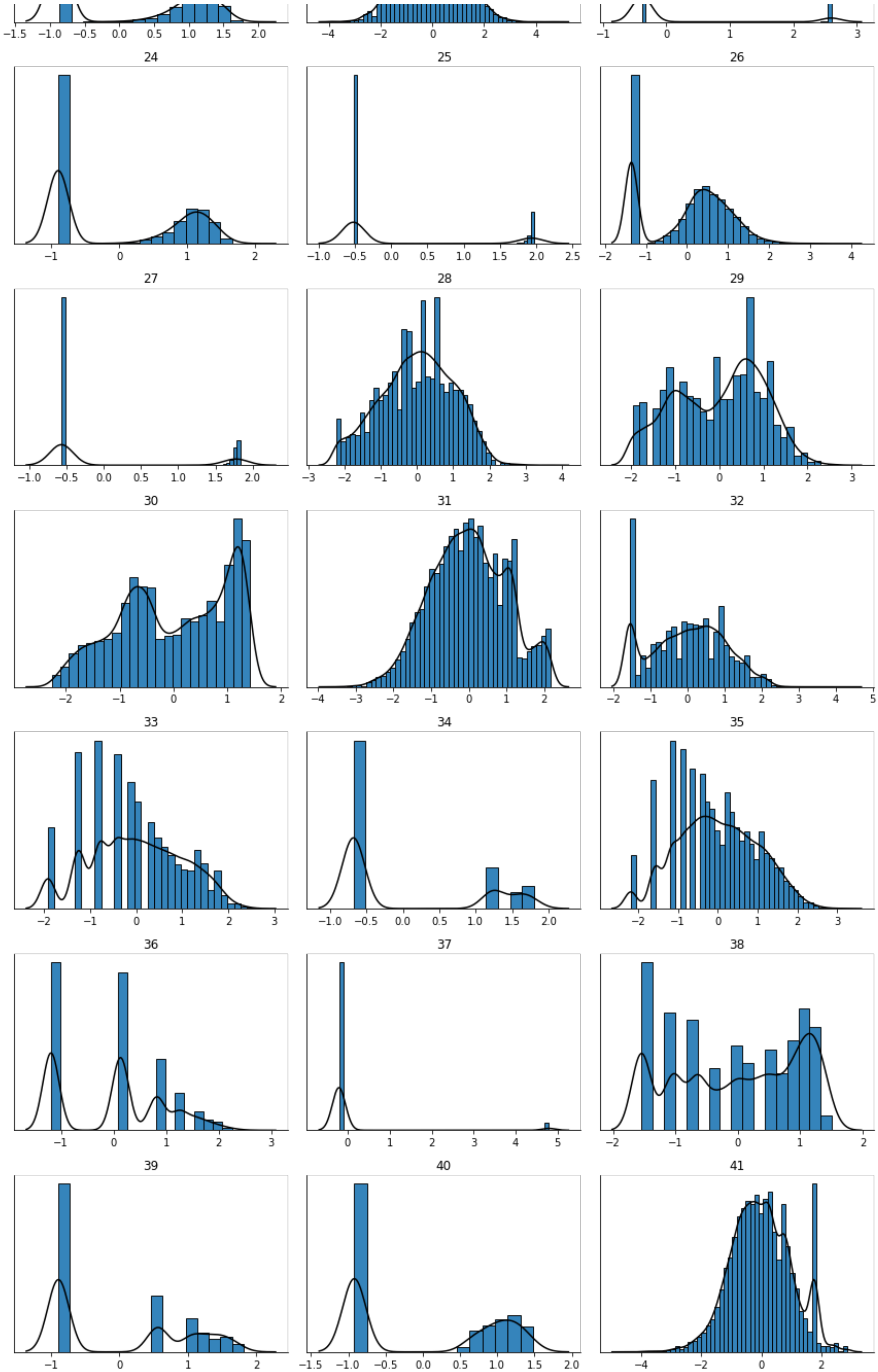
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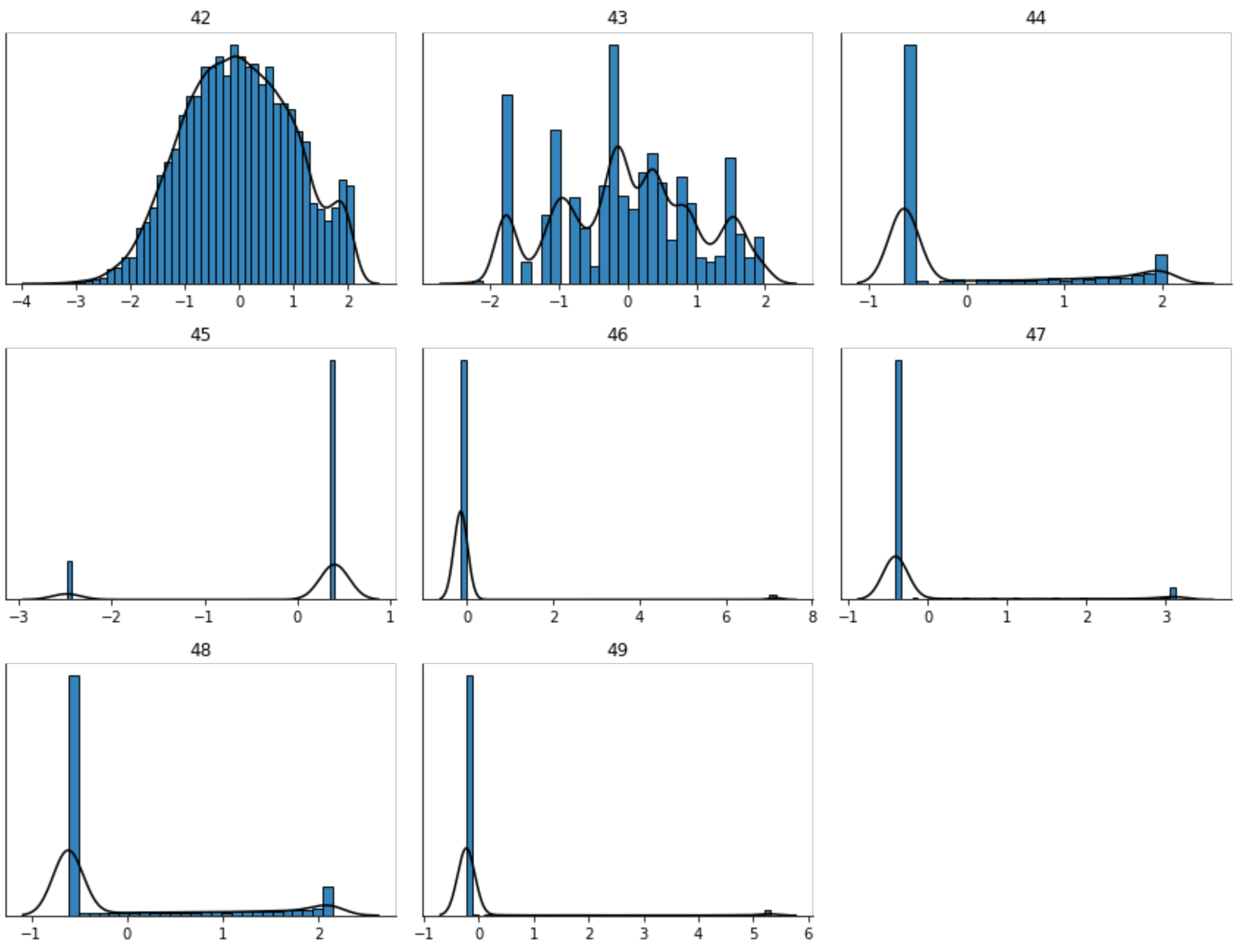

3. Linear Model

Elastic Net Cross Validation and Model

In [21]:

```
from sklearn.linear_model import LogisticRegression

lr_cv = LogisticRegression(penalty = 'elasticnet', solver = 'saga', l1_rat
```

In [22]:

```
lr_cv.fit(X_train,np.ravel(y_train))
```

Out[22]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True
,
                   intercept_scaling=1, l1_ratio=1, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='elasticnet',
                   random_state=None, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [23]:

```
lr_cv.l1_ratio
```

Out[23]:

```
1
```

Validation Error rate

In [24]:
```
lrpredv = lr_cv.predict(X_val)
```

In [25]:
```
sum(abs(y_val - lrpredv))/len(y_val)
```

Out[25]:
```
0.1391337677270985
```

Validation scores

In [26]:
```
from sklearn.metrics import classification_report

print(classification_report(y_val, lrpredv))
```

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      2184
           1       0.63      0.35      0.45       425

    accuracy                           0.86      2609
   macro avg       0.76      0.66      0.69      2609
weighted avg       0.84      0.86      0.84      2609
```

Test Error rate

In [27]:
```
lrpred = lr_cv.predict(X_test)
```

In [28]:
```
sum(abs(y_test - lrpred))/len(y_test)
```

Out[28]:
```
0.14155933762649495
```

Test scores

In [29]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, lrpred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      7252
           1       0.65      0.32      0.43      1444

    accuracy                           0.86      8696
   macro avg       0.76      0.64      0.67      8696
weighted avg       0.84      0.86      0.84      8696
```

4. Tree-based model

XGBoost

In [30]:
```
from skopt.space import Real, Categorical, Integer
from skopt import BayesSearchCV
```

In [31]:
```
from xgboost import XGBClassifier

model = XGBClassifier()

search_space = {
    'reg_lambda': Real(1e-10, 1e12, 'log-uniform'),
    'learning_rate': Real(0.005, 0.1),
    'n_estimators' : Integer(100, 5000),
    'max_depth' : Integer(2, 8),
    'subsample' : Real(0.5, 1.0),
    'colsample_bytree' : Real(0.25, 1.0),
}

xgb_opt =  BayesSearchCV(model, search_space, cv = 5,  n_iter= 8, scoring =
```

In [32]:
```
print('Warning: Optimising and fitting XGBoost will take at least 40 minute
optimise = str(input('Would you like to optimise and fit XGBoost? Answer \

if optimise.lower() == 'c':
    model = xgb_opt.fit(X_train, y_train)
    xgb_opt.best_params_
```

```
Warning: Optimising and fitting XGBoost will take at least 40 minutes.

[12:35:44] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6
691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:106
1: Starting in XGBoost 1.3.0, the default evaluation metric used with the o
bjective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitl
y set eval_metric if you'd like to restore the old behavior.
```

In [33]:
```
xgb_opt.best_params_
```

Out[33]:
```
OrderedDict([('colsample_bytree', 0.7012486140201625),
             ('learning_rate', 0.01730002785667402),
             ('max_depth', 3),
             ('n_estimators', 629),
             ('reg_lambda', 2.750046458491444e-08),
             ('subsample', 0.5462477145579053)])
```

In [34]:
```
xgboost = xgb_opt.best_estimator_
```

In [37]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
kf=KFold(5)
score = cross_val_score(xgboost, X_val, y_val, cv=kf, scoring = 'neg_mean_s
print("xgboost: {:.4f} ({:.4f})".format(score.mean(), score.std()))
print(np.sqrt(-score)) #scores for each fold
```

```
[12:38:32] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6
691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:106
1: Starting in XGBoost 1.3.0, the default evaluation metric used with the o
bjective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitl
y set eval_metric if you'd like to restore the old behavior.
[12:38:33] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6
691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:106
1: Starting in XGBoost 1.3.0, the default evaluation metric used with the o
bjective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitl
y set eval_metric if you'd like to restore the old behavior.
[12:38:33] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6
691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:106
1: Starting in XGBoost 1.3.0, the default evaluation metric used with the o
bjective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitl
y set eval_metric if you'd like to restore the old behavior.
[12:38:34] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6
691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:106
1: Starting in XGBoost 1.3.0, the default evaluation metric used with the o
bjective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitl
y set eval_metric if you'd like to restore the old behavior.
[12:38:35] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6
691-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:106
1: Starting in XGBoost 1.3.0, the default evaluation metric used with the o
bjective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitl
y set eval_metric if you'd like to restore the old behavior.
xgboost: -0.1468 (0.0124)
[0.41291414 0.37651355 0.38156765 0.37651355 0.36654741]
```

Validation Error rate

In [38]:
```
xgbpredv = xgboost.predict(X_val)
```

In [39]:
```
xgbpredv.shape
```

Out[39]:
```
(2609,)
```

In [40]:
```
sum(abs(y_val - xgbpredv))/len(y_val)
```

Out[40]:
```
0.14105021080873897
```

Validation scores

In [41]:
```
from sklearn.metrics import classification_report

print(classification_report(y_val, xgbpredv))
```

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      2184
           1       0.63      0.32      0.43       425

    accuracy                           0.86      2609
   macro avg       0.76      0.64      0.67      2609
weighted avg       0.84      0.86      0.84      2609
```

Test Error rate

In [42]:
```
xgbpred = xgboost.predict(X_test)
```

In [43]:
```
sum(abs(y_test - xgbpred))/len(y_test)
```

Out[43]: 0.1424793008279669

Test scores

In [44]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, xgbpred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.97      0.92      7252
           1       0.67      0.28      0.40      1444

    accuracy                           0.86      8696
   macro avg       0.77      0.63      0.66      8696
weighted avg       0.84      0.86      0.83      8696
```

5. Neural Network

In [45]:

```
from tensorflow import keras
from tensorflow.keras import layers

# Inputs
inputs = keras.Input(shape=(X_train.shape[1],))

# Hidden layers
# The SELU slows things down quite a bit, consider changing to ReLU if thi
# Use the Lecun normal initialisation with the SELU
hidden1 = layers.Dense(128, kernel_initializer='lecun_normal', activation=
hidden2 = layers.Dense(128, kernel_initializer='lecun_normal', activation=
hidden3  = layers.Dense(128, kernel_initializer='lecun_normal', activation

# Output layers
output = layers.Dense(1, activation='sigmoid')(hidden3)

# Build model
dfn = keras.Model(inputs=inputs, outputs=output)
dfn.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 50)]              0
_________________________________________________________________
dense (Dense)                (None, 128)               6528
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_2 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 39,681
Trainable params: 39,681
Non-trainable params: 0
_________________________________________________________________
```

In [46]:

```
from tensorflow.keras.optimizers import Adam

# These are additional metrics that we will keep track of during training
metrics = [
    keras.metrics.Recall(name="sensitivity"),
    keras.metrics.Precision(name="precision"),
]

# A callback is an object that implements actions at different stages of t
# This callback will stop training when the validation error does not impr
# The restore best weights option returns the model from the best epoch up
earlystopping = keras.callbacks.EarlyStopping(monitor='val_loss', restore_l
                                              patience=5, verbose=1)

# We set the learning rate for the Adam optimizer to
dfn.compile(loss='binary_crossentropy', optimizer=Adam(1e-3), metrics=metri
dfn.fit(X_train,
        y_train,
        epochs=50,
        batch_size=1024,
        validation_data =(X_val, y_val),
        callbacks = [earlystopping],
        verbose=2)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to fi
nd data adapter that can handle input: <class 'pandas.core.frame.DataFrame'
>, <class 'NoneType'>
Train on 10435 samples, validate on 2609 samples
Epoch 1/50
10435/10435 - 1s - loss: 0.5744 - sensitivity: 0.5172 - precision: 0.2904 -
val_loss: 0.4091 - val_sensitivity: 0.3671 - val_precision: 0.4419
Epoch 2/50
10435/10435 - 0s - loss: 0.3890 - sensitivity: 0.2560 - precision: 0.4491 -
val_loss: 0.3576 - val_sensitivity: 0.2235 - val_precision: 0.5864
Epoch 3/50
10435/10435 - 0s - loss: 0.3520 - sensitivity: 0.2497 - precision: 0.5769 -
val_loss: 0.3349 - val_sensitivity: 0.3176 - val_precision: 0.5947
Epoch 4/50
10435/10435 - 0s - loss: 0.3343 - sensitivity: 0.3106 - precision: 0.6197 -
val_loss: 0.3283 - val_sensitivity: 0.3929 - val_precision: 0.5943
Epoch 5/50
10435/10435 - 0s - loss: 0.3279 - sensitivity: 0.3731 - precision: 0.6069 -
val_loss: 0.3289 - val_sensitivity: 0.3082 - val_precision: 0.6179
Epoch 6/50
10435/10435 - 0s - loss: 0.3222 - sensitivity: 0.3255 - precision: 0.6495 -
val_loss: 0.3257 - val_sensitivity: 0.3812 - val_precision: 0.6000
Epoch 7/50
10435/10435 - 0s - loss: 0.3176 - sensitivity: 0.3525 - precision: 0.6511 -
val_loss: 0.3252 - val_sensitivity: 0.3906 - val_precision: 0.6171
Epoch 8/50
10435/10435 - 0s - loss: 0.3122 - sensitivity: 0.3594 - precision: 0.6667 -
val_loss: 0.3215 - val_sensitivity: 0.3482 - val_precision: 0.6167
Epoch 9/50
10435/10435 - 0s - loss: 0.3118 - sensitivity: 0.3886 - precision: 0.6547 -
val_loss: 0.3225 - val_sensitivity: 0.3788 - val_precision: 0.6075
Epoch 10/50
10435/10435 - 0s - loss: 0.3093 - sensitivity: 0.3594 - precision: 0.6534 -
val_loss: 0.3277 - val_sensitivity: 0.2565 - val_precision: 0.6337
Epoch 11/50
10435/10435 - 0s - loss: 0.3103 - sensitivity: 0.3657 - precision: 0.6622 -
val_loss: 0.3309 - val_sensitivity: 0.4212 - val_precision: 0.5701
Epoch 12/50
10435/10435 - 0s - loss: 0.3041 - sensitivity: 0.3823 - precision: 0.6734 -
val_loss: 0.3290 - val_sensitivity: 0.3529 - val_precision: 0.6024
Epoch 13/50
Restoring model weights from the end of the best epoch.
10435/10435 - 0s - loss: 0.2988 - sensitivity: 0.3938 - precision: 0.6853 -
val_loss: 0.3271 - val_sensitivity: 0.3882 - val_precision: 0.5769
Epoch 00013: early stopping
```

Out[46]:
```
<tensorflow.python.keras.callbacks.History at 0x7fb1c9185fd0>
```

Validation error rate

In [47]:
```
dfnpredv = dfn.predict(X_val)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to fi
nd data adapter that can handle input: <class 'pandas.core.frame.DataFrame'
>, <class 'NoneType'>
```

In [48]:
```
dfnpredv
```

Out[48]:
```
array([[0.03214273],
       [0.10125357],
       [0.27300125],
       ...,
       [0.00742921],
       [0.04045948],
       [0.03628386]], dtype=float32)
```

In [49]:
```
dfnpredv.ravel()
```

Out[49]:
```
array([0.03214273, 0.10125357, 0.27300125, ..., 0.00742921, 0.04045948,
       0.03628386], dtype=float32)
```

In [50]:
```
sum(abs(y_val - dfnpredv.ravel()))/len(y_val)
```

Out[50]:
```
0.20232790866606123
```

Validation scores

In [51]:

```
from sklearn.metrics import accuracy_score, recall_score, precision_score
from sklearn.metrics import confusion_matrix, log_loss, average_precision_s

columns=['Relative Risk', 'Error rate', 'Sensitivity', 'Specificity',
         'Precision', 'Average Precision','F1 Score']
rows=['DFN']
results=pd.DataFrame(0.0, columns=columns, index=rows)

methods=[dfn]

lfp = 1
lfn = 10
tau = lfp/(lfp+lfn)

for i, method in enumerate(methods):

    if method in [dfn]:
        y_prob = method.predict(X_val)
    else:
        y_prob = method.predict_proba(X_val)[:,1]

    y_pred = (y_prob>tau).astype(int)

    tn, fp, fn, tp = confusion_matrix(y_val, y_pred).ravel()

    results.iloc[i,0]=  (fp*lfp+fn*lfn)/len(y_val)
    results.iloc[i,1]=  1 - accuracy_score(y_val, y_pred)
    results.iloc[i,2]=  tp/(tp+fn)
    results.iloc[i,3]=  tn/(tn+fp)
    results.iloc[i,4]=  precision_score(y_val, y_pred)
    results.iloc[i,5]=  average_precision_score(y_val, y_prob)
    results.iloc[i,6]=  f1_score(y_val, y_pred)

results.iloc[:,0] /= results.iloc[0,0]
results.round(3)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to fi
nd data adapter that can handle input: <class 'pandas.core.frame.DataFrame'
>, <class 'NoneType'>
```

Out[51]:

	Relative Risk	Error rate	Sensitivity	Specificity	Precision	Average Precision	F1 Score
DFN	1.0	0.351	0.906	0.598	0.305	0.544	0.456

6. Additional models

6.1 Code for the best additional model

KNeighbors Classifier

In [52]:
```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()

from sklearn.model_selection import GridSearchCV

param_grid = {
    'p': (1,2),
    'n_neighbors': (3,5,7,9,11),
    'weights' : ('uniform', 'distance'),
    'metric' : ('euclidean', 'manhattan')
}

grid_cv_obj = GridSearchCV(model, param_grid)
grid_cv_obj.fit(X_train, y_train)
```

Out[52]:
```
GridSearchCV(cv=None, error_score=nan,
             estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30,
                                            metric='minkowski',
                                            metric_params=None, n_jobs=None
,
                                            n_neighbors=5, p=2,
                                            weights='uniform'),
             iid='deprecated', n_jobs=None,
             param_grid={'metric': ('euclidean', 'manhattan'),
                         'n_neighbors': (3, 5, 7, 9, 11), 'p': (1, 2),
                         'weights': ('uniform', 'distance')},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [54]:
```
knn = grid_cv_obj.best_estimator_
print(knn)
print(grid_cv_obj.best_params_)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='manhattan',
                     metric_params=None, n_jobs=None, n_neighbors=11, p=1,
                     weights='uniform')
{'metric': 'manhattan', 'n_neighbors': 11, 'p': 1, 'weights': 'uniform'}
```

In [55]:
```
score = cross_val_score(knn, X_val, y_val, cv=kf, scoring = 'neg_mean_squa
print("knn: {:.4f} ({:.4f})".format(score.mean(), score.std()))
print(np.sqrt(-score)) #scores for each fold
```

```
knn: -0.1587 (0.0102)
[0.41752785 0.38655567 0.40114778 0.4035285  0.38193366]
```

Validation error rate

In [56]:
```
knnpredv = knn.predict(X_val)
```

In [57]:
```
sum(abs(y_val - knnpredv))/len(y_val)
```

Out[57]:
```
0.15753162131084708
```

Validation scores

In [58]:
```
from sklearn.metrics import classification_report

print(classification_report(y_val, knnpredv))
```

```
              precision    recall  f1-score   support

           0       0.87      0.96      0.91      2184
           1       0.54      0.24      0.33       425

    accuracy                           0.84      2609
   macro avg       0.70      0.60      0.62      2609
weighted avg       0.81      0.84      0.82      2609
```

Test error rate

In [59]:
```
knnpred = knn.predict(X_test)
```

In [60]:
```
sum(abs(y_test - knnpred))/len(y_test)
```

Out[60]: 0.15788868445262189

Test scores

In [61]:
```
from sklearn.metrics import classification_report

print(classification_report(y_test, knnpred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.97      0.91      7252
           1       0.57      0.20      0.30      1444

    accuracy                           0.84      8696
   macro avg       0.71      0.59      0.61      8696
weighted avg       0.81      0.84      0.81      8696
```

7. Model selection

7.1 Code

Simple benchmark

In [62]:
```
from sklearn.linear_model import LogisticRegression
LogR = LogisticRegression(solver='liblinear', random_state=0)
LogR.fit(X_train, y_train)
```

Out[62]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True
,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='liblinear', tol=0.0001, verbose=
0,
                   warm_start=False)
```

Validation error rate

In [63]:
```
LogRpredv = LogR.predict(X_val)
```

In [64]:
```
sum(abs(y_val - LogRpredv))/len(y_val)
```

Out[64]:
```
0.1399003449597547
```

7.2 Results

Code that displays any tables should go here.

Validation Scores

Benchmark

In [65]:
```
print(classification_report(y_val, LogRpredv))
```

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      2184
           1       0.63      0.35      0.45       425

    accuracy                           0.86      2609
   macro avg       0.76      0.65      0.68      2609
weighted avg       0.84      0.86      0.84      2609
```

Elastic Net

In [66]:
```
print(classification_report(y_val, lrpredv))
```

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      2184
           1       0.63      0.35      0.45       425

    accuracy                           0.86      2609
   macro avg       0.76      0.66      0.69      2609
weighted avg       0.84      0.86      0.84      2609
```

XGBoost

In [67]:
```
print(classification_report(y_val, xgbpredv))
```

```
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      2184
           1       0.63      0.32      0.43       425

    accuracy                           0.86      2609
   macro avg       0.76      0.64      0.67      2609
weighted avg       0.84      0.86      0.84      2609
```

Deep Feedforward Network

In [68]:

```
from sklearn.metrics import accuracy_score, recall_score, precision_score
from sklearn.metrics import confusion_matrix, log_loss, average_precision_s

columns=['Relative Risk', 'Error rate', 'Sensitivity', 'Specificity',
         'Precision', 'Average Precision','F1 Score']
rows=['DFN']
results=pd.DataFrame(0.0, columns=columns, index=rows)

methods=[dfn]

lfp = 1
lfn = 10
tau = lfp/(lfp+lfn)

for i, method in enumerate(methods):

    if method in [dfn]:
        y_prob = method.predict(X_val)
    else:
        y_prob = method.predict_proba(X_val)[:,1]

    y_pred = (y_prob>tau).astype(int)

    tn, fp, fn, tp = confusion_matrix(y_val, y_pred).ravel()

    results.iloc[i,0]=  (fp*lfp+fn*lfn)/len(y_val)
    results.iloc[i,1]=  1 - accuracy_score(y_val, y_pred)
    results.iloc[i,2]=  tp/(tp+fn)
    results.iloc[i,3]=  tn/(tn+fp)
    results.iloc[i,4]=  precision_score(y_val, y_pred)
    results.iloc[i,5]=  average_precision_score(y_val, y_prob)
    results.iloc[i,6]=  f1_score(y_val, y_pred)

results.iloc[:,0] /= results.iloc[0,0]
results.round(3)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to fi
nd data adapter that can handle input: <class 'pandas.core.frame.DataFrame'
>, <class 'NoneType'>
```

Out[68]:

	Relative Risk	Error rate	Sensitivity	Specificity	Precision	Average Precision	F1 Score
DFN	1.0	0.351	0.906	0.598	0.305	0.544	0.456

kNN Classifier

In [69]:

```
print(classification_report(y_val, knnpredv))
```

```
              precision    recall  f1-score   support

           0       0.87      0.96      0.91      2184
           1       0.54      0.24      0.33       425

    accuracy                           0.84      2609
   macro avg       0.70      0.60      0.62      2609
weighted avg       0.81      0.84      0.82      2609
```

8. Model Evaluation

8.1 Code

Benchmark test error rate

In [70]:
```
LogRpred = LogR.predict(X_test)
sum(abs(y_test - LogRpred))/len(y_test)
```

Out[70]:
```
0.14132934682612697
```

8.2 Results

Code that displays any tables should go here.

Test set results

Benchmark

In [71]:
```
print(classification_report(y_test, LogRpred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      7252
           1       0.65      0.32      0.43      1444

    accuracy                           0.86      8696
   macro avg       0.76      0.64      0.67      8696
weighted avg       0.84      0.86      0.84      8696
```

Elastic Net

In [72]:
```
print(classification_report(y_test, lrpred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      7252
           1       0.65      0.32      0.43      1444

    accuracy                           0.86      8696
   macro avg       0.76      0.64      0.67      8696
weighted avg       0.84      0.86      0.84      8696
```

XGBoost

In [73]:

```
print(classification_report(y_test, xgbpred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.97      0.92      7252
           1       0.67      0.28      0.40      1444

    accuracy                           0.86      8696
   macro avg       0.77      0.63      0.66      8696
weighted avg       0.84      0.86      0.83      8696
```

Deep Feedforward Network

In [74]:

```
dfnpred = dfn.predict(X_test)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to fi
nd data adapter that can handle input: <class 'pandas.core.frame.DataFrame'
>, <class 'NoneType'>
```

In [75]:

```
sum(abs(y_test - dfnpred.ravel()))/len(y_test)
```

Out[75]:

```
0.2075945645461087
```

In [76]:
```
from sklearn.metrics import accuracy_score, recall_score, precision_score
from sklearn.metrics import confusion_matrix, log_loss, average_precision_s

columns=['Relative Risk', 'Error rate', 'Sensitivity', 'Specificity',
         'Precision', 'Average Precision','F1 Score']
rows=['DFN']
results=pd.DataFrame(0.0, columns=columns, index=rows)

methods=[dfn]

lfp = 1
lfn = 10
tau = lfp/(lfp+lfn)

for i, method in enumerate(methods):

    if method in [dfn]:
        y_prob = method.predict(X_test)
    else:
        y_prob = method.predict_proba(X_test)[:,1]

    y_pred = (y_prob>tau).astype(int)

    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()

    results.iloc[i,0]=  (fp*lfp+fn*lfn)/len(y_test)
    results.iloc[i,1]=  1 - accuracy_score(y_test, y_pred)
    results.iloc[i,2]=  tp/(tp+fn)
    results.iloc[i,3]=  tn/(tn+fp)
    results.iloc[i,4]=  precision_score(y_test, y_pred)
    results.iloc[i,5]=  average_precision_score(y_test, y_prob)
    results.iloc[i,6]=  f1_score(y_test, y_pred)

results.iloc[:,0] /= results.iloc[0,0]
results.round(3)
```

```
WARNING:tensorflow:Falling back from v2 loop because of error: Failed to fi
nd data adapter that can handle input: <class 'pandas.core.frame.DataFrame'
>, <class 'NoneType'>
```

Out[76]:

	Relative Risk	Error rate	Sensitivity	Specificity	Precision	Average Precision	F1 Score
DFN	1.0	0.359	0.889	0.592	0.302	0.519	0.451

kNN Classifier

In [77]:
```
print(classification_report(y_test, knnpred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.97      0.91      7252
           1       0.57      0.20      0.30      1444

    accuracy                           0.84      8696
   macro avg       0.71      0.59      0.61      8696
weighted avg       0.81      0.84      0.81      8696
```