Stock Trades by Members of the US House of Representatives

Summary of Findings

Introduction

Model

Predict if a transaction has capitial gains over 200 USD

In this project, we want to estimate if a transaction will have capital gains exceeding $200 using the provided dataset. We'll need to create a classification model to do this. There are many different classifying models, such as **Decision Tree**, **Random Forest**, **K Mean Clustering**, etc. A boolean column called `cap_gains_over_200_usd` in the transaction dataset will be True if a transaction contains capital gains over $200 USD. This would be the output label we would be using, and so this made our prediction to be a classifciation problem. We would take into account several columns in our transaction dataset for the input features. As both our baseline model and final model made advantage of several features.

Evaluation

For evaulation of our model, we have chosen to use the following metrics:

- Accuracy score

$$\text{accuracy} = \frac{\text{\# data points classified correctly}}{\text{\# data points}} = \frac{TP + TN}{TP + FP + FN + TN}$$

- Precision score

$$\text{precision} = \frac{TP}{\text{\# predicted positive}} = \frac{TP}{TP + FP}$$

- Recall score

$$\text{recall} = \frac{TP}{\text{\# actually positive}} = \frac{TP}{TP + FN}$$

Baseline Model

Baseline Model: [disclosure_year, disclosure_date(1-6, 7-12)binarizer, owner(one_hot_encode), type, amount(turn to cat), party(stdByGroup with amount)]

For the baseline model, we believe that the features of `disclosure_year`, `transaction_date`, `owner`, `type`, and `amount` are related to the output of `cap_gain_over_200`.

Total of 7 features are used in the baseline model:

- `disclosure_year`: Categorical ordinal
- `transaction_date`: Categorical ordinal

- `owner` : Categorical nominal
- `type` : Categorical nominal
- `amount` : Quantitative

In the pipeline, we pre-process the input features with the following steps:

1. One-hot encode `disclosure_year` , `owner` and `party` columns.
2. Extract the month of `transaction_date` and then using `Binarizer` to transform it into a boolean Series where month \le is `False` , otherwise is `True` .
3. Transform the `amount` column into a quantittative feature by calculating the average of thresholds.

Performance

Then we process to performing `GridSearchCV` to find out the best parameters for `RandomForestClassifer` . Using the best parameters we have got, our model has the following performance metrics:

Confusion matrix

	Actually True	Actually False
Predict True	3664	28
Predict False	200	27

- **Train_Score** : 93.96%
- **Test_Score** : 94.18%
- **Accuracy** : 94.36%
- **Precision** : 55%
- **Recalls** : 14.54%

Final Model

In the Baseline Model: we discovered relatively high accuracy along with high training score and testing score. However, the precision and recalls rate indicate a problem. We then restimated the datasets in the `cap_gain_over_200` and realized unbalanced with True and False ratio of 1:15. With this idea in mind, we can generalize what our baseline model is doing is simply guessing False most of the time and that generate a biased!

For the Final model, we still believe that the features of `disclosure_year` , `transaction_date` , `owner` , `type` , `amount` and `party` are related to the output of `cap_gain_over_200` so keeping features unchanged.

The approaches we took to eliminate the biasness and perform training are as follow:

Total of 7 features are used in the baseline model:

- `disclosure_year` : Categorical ordinal
- `transaction_date` : Categorical ordinal
- `owner` : Categorical nominal
- `type` : Categorical nominal
- `amount` : Quantitative
- `party` : Categorical nominal

1. Use the `StdScalerByGroup` to calculate the standardized amount of every transaction by their coresponding party.
2. Balance the True False ratio in `cap_gain_over_200` through imblearn. After the balanced, True False ratio becomes 1:1
3. Follow the same pre-process procedures we done in Baseline model to prepared the datasets for analysis.
4. Fit pipline with same steps in baseline.

Using the best parameters we have got, our model has the following Scores and performance metrics:

Confusion matrix

	Actually True	Actually False
Predict True	4408	4
Predict False	149	3534

- **Train_Score** : 87.71%
- **Test_Score** : 87.53%
- **Accuracy** : 87.64%
- **Precision** : 82.30%
- **Recalls** : 95.95%

Although the score offsets by the increase in observations, but it also leviates the precision and recalls. We believed Final model gives a better explantation than the Baseline model without bias. This Model seems to be GREAT!! Next is to see how fair is this model generated.

Fairness Evaluation

However, in terms of fairness our models might introduce bias into the prediction. When running permutation test with the features include in the final model, the red line indicates the score obtained by the classifier on the original data. The score is much better than those obtained by using permuted data and the p-value is thus very low. This indicates that there is a low likelihood that this good score would be obtained by chance alone. It provides evidence that the transaction datasets contains real dependency between features and labels and the classifier was able to utilize this to obtain good results.

Code

In [2]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution figures
```

In [3]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import Binarizer
from sklearn.preprocessing import FunctionTransformer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
```

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
```

In [4]:
```
transactions = pd.read_csv('data/congress_trading.csv')
transactions.head()
```

Out[4]:

	Unnamed: 0	disclosure_year	disclosure_date	transaction_date	owner	ticker	asset_description	typ
0	0	2021	2021-10-04	2021-09-27	joint	BP	BP plc	purchas
1	1	2021	2021-10-04	2021-09-13	joint	XOM	Exxon Mobil Corporation	purchas
2	2	2021	2021-10-04	2021-09-10	joint	ILPT	Industrial Logistics Properties Trust - Common...	purchas
3	3	2021	2021-10-04	2021-09-28	joint	PM	Phillip Morris International Inc	purchas
4	4	2021	2021-10-04	2021-09-17	self	BLK	BlackRock Inc	sale_parti

Baseline Model

Baseline Model: [disclosure_year, disclosure_date(1-6, 7-12)binarizer, owner(one_hot_encode), type, amount(turn to cat), party(stdByGroup with amount)]

In [5]:
```
import pandas as pd
from sklearn.base import BaseEstimator, TransformerMixin

class StdScalerByGroup(BaseEstimator, TransformerMixin):

    def __init__(self):
        pass

    def preprocess_(self, df):
        for col in df.columns[1:]:
            df[col] = (df[col]
                       .str.replace(r'[+\-$,]', '', regex=True)
                       .str.replace(r'\s+', ' ', regex=True)
                       .str.strip()
                       .str.split()
                       .apply(lambda x: sum(map(int, x)) // len(x)))
        return df

    def fit(self, X, y=None):
        """
        :Example:
        >>> cols = {'g': ['A', 'A', 'B', 'B'], 'c1': [1, 2, 2, 2], 'c2': [3, 1, 2, 0]}
        >>> X = pd.DataFrame(cols)
        >>> std = StdScalerByGroup().fit(X)
        >>> std.grps_ is not None
        True
        """
        # X might not be a pandas DataFrame (e.g. a np.array)
        df = self.preprocess_(pd.DataFrame(X))
```

```
        # Compute and store the means/standard-deviations for each column (e.g. 'c1' and
        # for each group (e.g. 'A', 'B', 'C').
        # (Our solution uses a dictionary)
        df_agg = df.groupby(df.columns[0]).agg(['mean', 'std'])
        self.grps_ = {(g, c): df_agg.loc[g, c]
                      for g in df_agg.index for c in df_agg.columns}

        return self

    def transform(self, X, y=None):
        """
        :Example:
        >>> cols = {'g': ['A', 'A', 'B', 'B'], 'c1': [1, 2, 3, 4], 'c2': [1, 2, 3, 4]}
        >>> X = pd.DataFrame(cols)
        >>> std = StdScalerByGroup().fit(X)
        >>> out = std.transform(X)
        >>> out.shape == (4, 2)
        True
        >>> np.isclose(out.abs(), 0.707107, atol=0.001).all().all()
        True
        """

        try:
            getattr(self, "grps_")
        except AttributeError:
            raise RuntimeError(
                "You must fit the transformer before tranforming the data!")

        # Hint: Define a helper function here!
        def helper2(df):
            grp_col = df.columns[0]
            grps = df[grp_col].unique()
            df_grps = df.groupby(grp_col)

            df_out = []
            for grp in grps:
                df_grp = df_grps.get_group(grp).iloc[:, 1:]
                for col in df_grp.columns:
                    df_grp[col] = (
                        df_grp[col] - self.grps_[(grp, (col, 'mean'))]) / self.grps_[(grp
                df_out.append(df_grp)
            return pd.concat(df_out).fillna(0)

        df = pd.DataFrame(X)

        return helper2(df)
```

In [6]:

```
X_bs = transactions[['disclosure_date','owner','type', 'party','amount']]
y_bs = transactions['cap_gains_over_200_usd']

X_tr_bs, X_ts_bs, y_tr_bs, y_ts_bs = train_test_split(X_bs, y_bs, test_size=0.25)

binarize_disclosure_date = Pipeline([
    ('trans_dis_date', FunctionTransformer(lambda x: (x.iloc[:,0].str.split('-', expand=T
    ('to_int', FunctionTransformer(lambda x: x.astype('int'))),
    ('binarize', Binarizer(threshold=6))
])

convert_amount = Pipeline([
    ('to_int', FunctionTransformer(lambda x: x.iloc[:,0].str.replace('$', '', regex=True)
    ('to', FunctionTransformer(lambda x: x.astype('int')))
])
```

```
preproc_base = ColumnTransformer(
    transformers = [
        ('disclosure_date', binarize_disclosure_date, ['disclosure_date']),
        ('owner_type', OneHotEncoder(), ['owner', 'type', 'party']),
        ('quant_amount', convert_amount, ['amount'])
    ]
)

pl_bs = Pipeline([
    ('pre', preproc_base),
    ('classifier', RandomForestClassifier(max_depth=10))
])

pl_bs.fit(X_tr_bs, y_tr_bs)
print('baseline_tr_score', pl_bs.score(X_tr_bs,y_tr_bs))
print('baseline_ts_score', pl_bs.score(X_ts_bs,y_ts_bs))
```

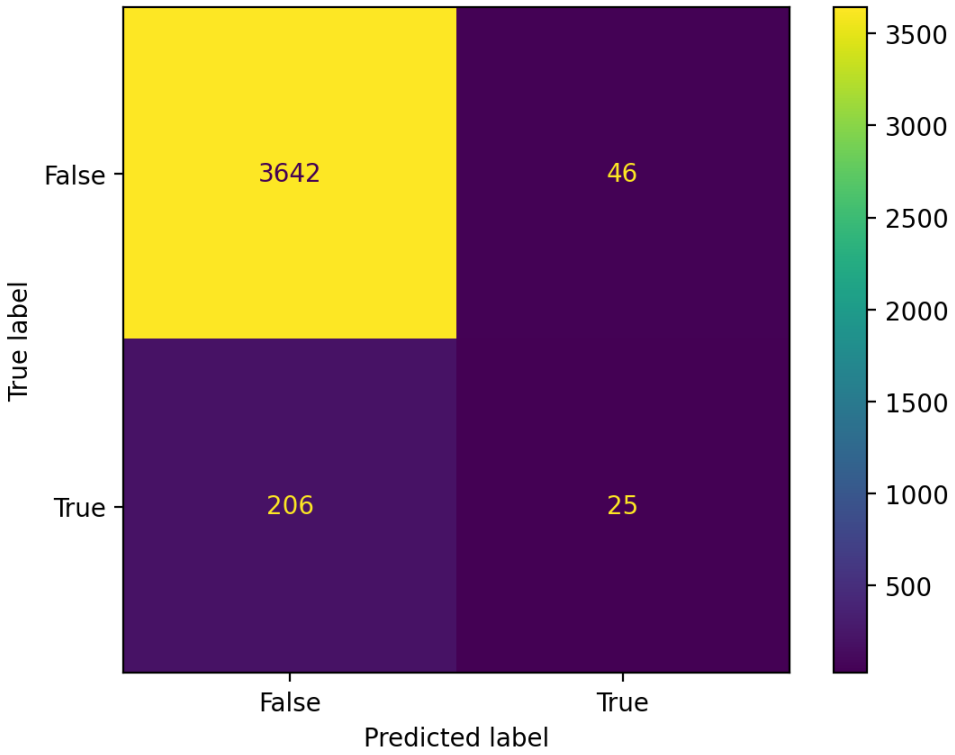
```
baseline_tr_score 0.9406210123351765
baseline_ts_score 0.9356978821127838
```

In [7]:

```
from sklearn import metrics

y_pred_bs = pl_bs.predict(X_ts_bs)
print('accuracy_score', metrics.accuracy_score(y_ts_bs, y_pred_bs))
print('precision_score', metrics.precision_score(y_ts_bs, y_pred_bs))
print('recalls_score', metrics.recall_score(y_ts_bs, y_pred_bs))
metrics.plot_confusion_matrix(pl_bs, X_ts_bs, y_ts_bs);
```

```
accuracy_score 0.9356978821127838
precision_score 0.352112676056338
recalls_score 0.10822510822510822
```

```
/Users/lijianpeng/opt/anaconda3/envs/dsc80/lib/python3.8/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```



Final Model

In [8]:
```
transactions['cap_gains_over_200_usd'].value_counts()
```

Out[8]:
```
False    14709
True       965
Name: cap_gains_over_200_usd, dtype: int64
```

In [9]:
```
!ln -s /user/project/functions.py functions.py
from stdByGroup import StdScalerByGroup
```

```
ln: functions.py: File exists
```

In [10]:
```
from imblearn.over_sampling import SMOTE
```

In [11]:
```
from imblearn.pipeline import Pipeline as iP

binarize_disclosure_date = Pipeline([
    ('trans_dis_date', FunctionTransformer(lambda x: (x.iloc[:,0].str.split('-', expand=T
    ('to_int', FunctionTransformer(lambda x: x.astype('int'))),
    ('binarize', Binarizer(threshold=6))
])

convert_amount = Pipeline([
    ('to_int', FunctionTransformer(lambda x: x.iloc[:,0].str.replace('$', '', regex=True)
    ('to', FunctionTransformer(lambda x: x.astype('int')))
])

preproc = ColumnTransformer(
    transformers = [
        ('disclosure_date', binarize_disclosure_date, ['disclosure_date']),
        ('owner_type', OneHotEncoder(), ['owner','type', 'party']),
        ('quant_amount', convert_amount, ['amount']),
        ('std_grps', StdScalerByGroup(), ['party', 'amount'])
    ]
)

ipl = iP([
    ('preproc', preproc),
    ('smt', SMOTE())
])

feature_df = transactions.drop(columns=['cap_gains_over_200_usd'])
label_df = transactions['cap_gains_over_200_usd']

trans_feature_df, trans_label_df = ipl.fit_resample(feature_df, label_df)
balance_transaction = pd.DataFrame(trans_feature_df)
```

In [18]:
```
# Baseline Model:
# [disclosure_year,  disclosure_date(1-6, 7-12)binarizer,  owner(one_hot_encode), type, a
X_fn = balance_transaction
y_fn = trans_label_df

X_tr, X_ts, y_tr, y_ts = train_test_split(X_fn, y_fn, test_size=0.25)

pl = Pipeline([
    ('classifier', RandomForestClassifier(max_depth=10))
])

pl.fit(X_tr, y_tr)
print('Train_sc',pl.score(X_tr, y_tr))
```

```
print('Test_sc',pl.score(X_ts, y_ts))
pl.score(balance_transaction, trans_label_df)
```

```
Train_sc 0.875356932420795
Test_sc 0.8769544527532291
```

Out[18]:
```
0.875756339655993
```

In [13]:
```
# hyperparameters = {
#     'classifier__max_depth': [2, 3, 4, 5, 7, 10, 13, 15, 18, None],
#     'classifier__min_samples_split': [2, 3, 5, 7, 10, 15, 20],
#     'classifier__criterion': ['gini', 'entropy']
#     }

# search = GridSearchCV(pl, hyperparameters, cv=5)
# search.fit(X_tr,y_tr)
# search.best_params_
```

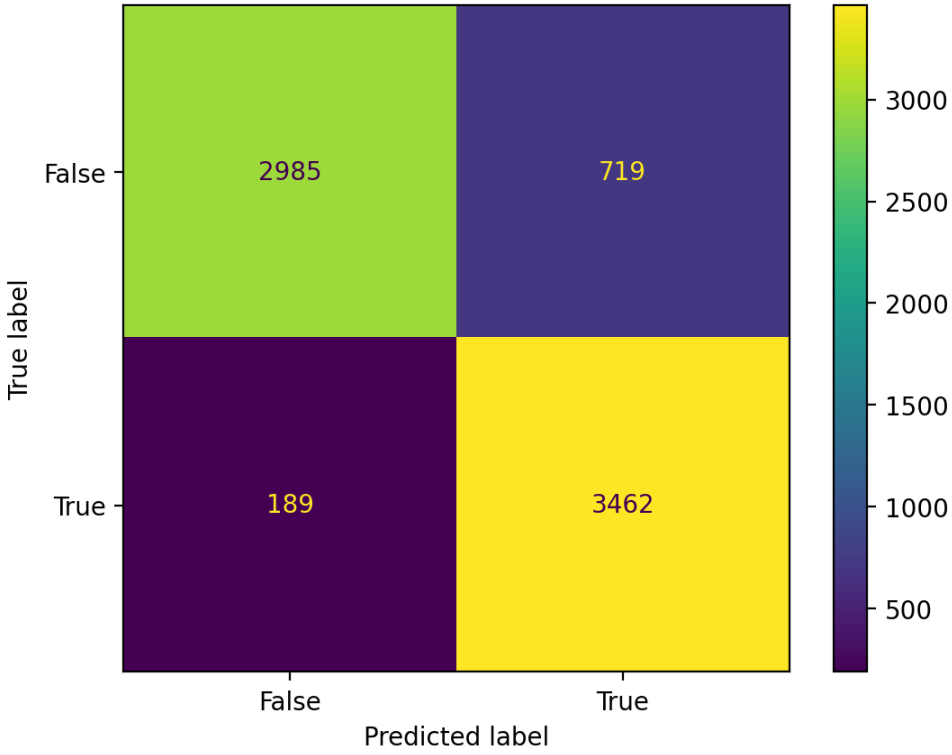
In [14]:
```
y_pred = pl.predict(X_tr)
y_pred
```

Out[14]:
```
array([ True,  True,  True, ...,  True,  True, False])
```

In [15]:
```
from sklearn import metrics

y_pred = pl.predict(X_ts)
print('accuracy_score', metrics.accuracy_score(y_ts, y_pred))
print('precision_score', metrics.precision_score(y_ts, y_pred))
print('recalls_score', metrics.recall_score(y_ts, y_pred))
metrics.plot_confusion_matrix(pl, X_ts, y_ts);
```

```
accuracy_score 0.8765465669612509
precision_score 0.8280315713944032
recalls_score 0.9482333607230896
```

```
/Users/lijianpeng/opt/anaconda3/envs/dsc80/lib/python3.8/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one of the class methods: ConfusionMatrixDisplay.from_predictions or ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

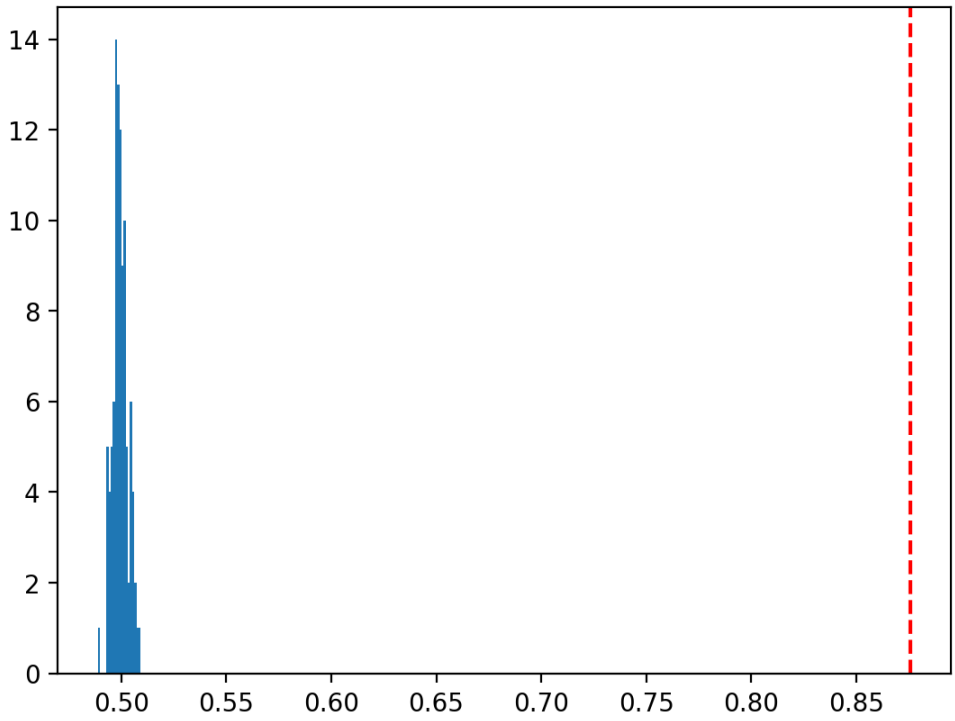


Fairness Evaluation

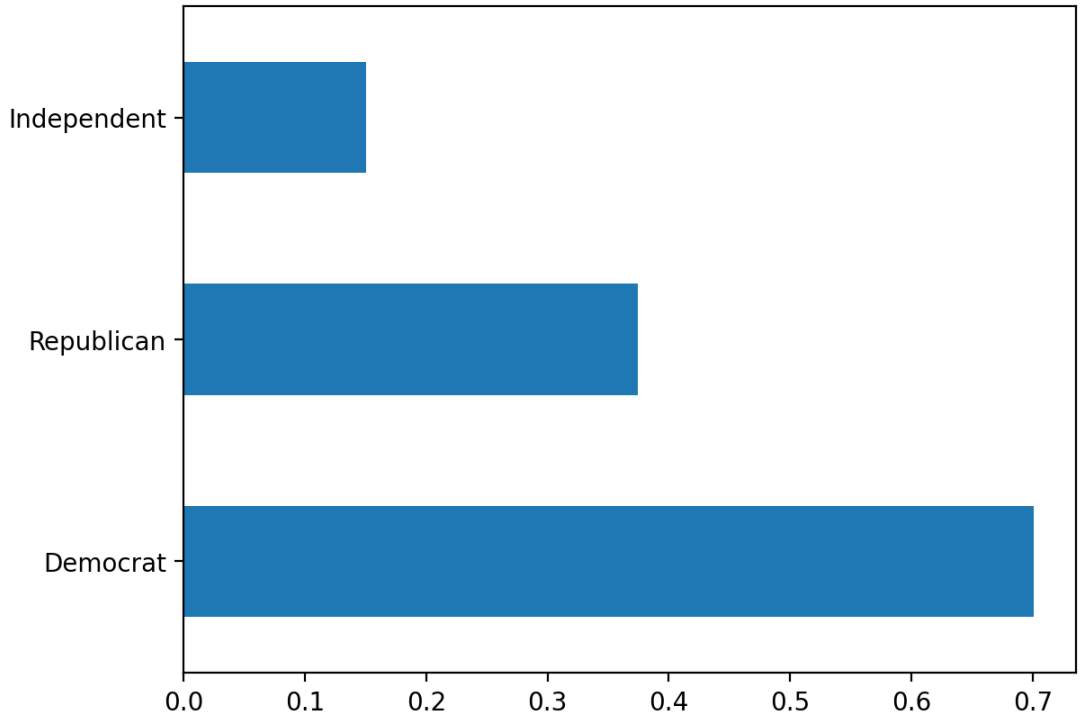
In [20]:
```
X = X_fn
y = y_fn

import numpy as np
import matplotlib.pyplot as plt

from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold, permutation_test_score
from sklearn import datasets

# svm = SVC(kernel='linear')
cv = StratifiedKFold(2)

score, permutation_scores, pvalue = permutation_test_score(
   pl , X, y, scoring="accuracy", cv=cv, n_permutations=100, n_jobs=1)

print("Classification score %s (pvalue : %s)" % (score, pvalue))

ax = plt.axes()
ax.hist(permutation_scores, 20, label='Permutation scores')
ax.axvline(pl.score(balance_transaction, trans_label_df), ls="--", color="r")
```

```
Classification score 0.7985247127608948 (pvalue : 0.009900990099009901)
```

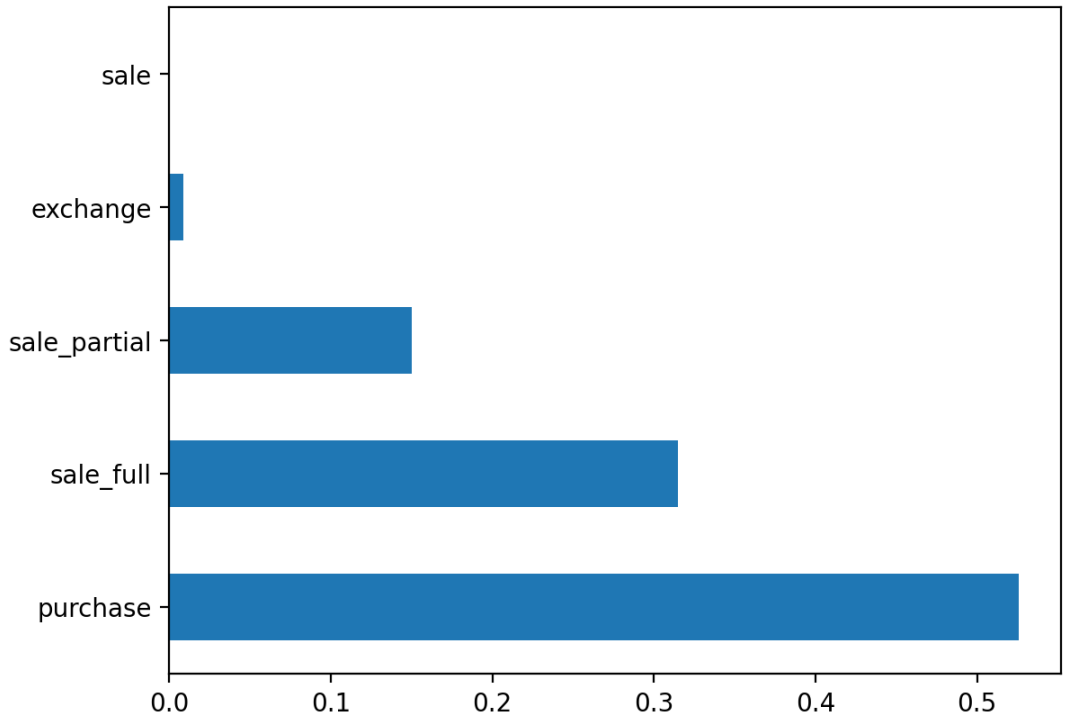
Out[20]:
```
<matplotlib.lines.Line2D at 0x7f94c0de37c0>
```



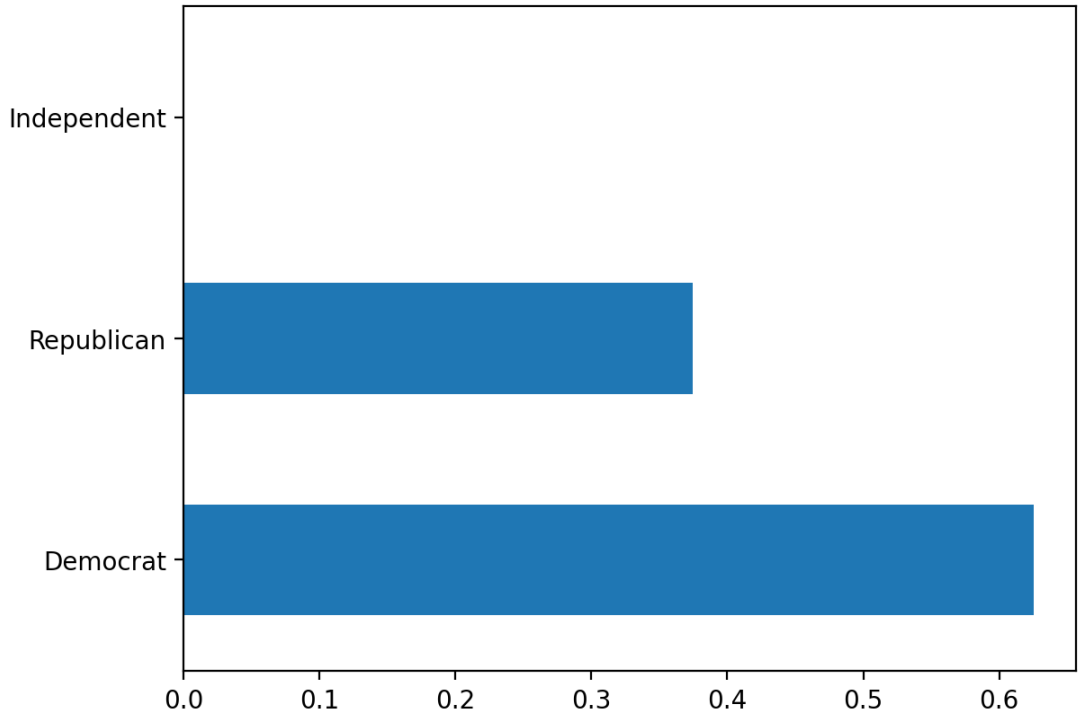
In [149…
```
transactions['amount'].value_counts(normalize=True).plot(kind='barh');
```



In [150…
```
transactions['type'].value_counts(normalize=True).plot(kind='barh');
```



In [151…
```
transactions['party'].value_counts(normalize=True).plot(kind='barh');
```



In [ ]:

In [ ]: