In [2]:
```
import numpy as np
import sklearn
import pandas as pd
import os
import time
import datetime
import matplotlib.pyplot as plt
```

In [3]:
```
# Mount google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [4]:
```
project_dir = "/content/drive/Shareddrives/data/CS188"
data = os.path.join(project_dir, "training_dataset_V3.csv")
```

In [5]:
```
raw_df = pd.read_csv(data)
```

In [6]:
```
raw_df.head()
```

Out[6]:

	Unnamed: 0	dt	weekday	year	id_driver	id_carrier_number	dim_carrier_type	dim_carrier_company_name	home_base_city	hom
0	0	2019-12-16	Monday	2019	21350	U0109015	Owner Operator	CA&F TRUCKING	Maywood	
1	1	2021-01-15	Friday	2021	36437	C0097727	Fleet	New opportunities inc	Los Angeles	
2	2	2019-12-26	Thursday	2019	19323	U0107081	Owner Operator	RAS	Compton	
3	3	2021-02-10	Wednesday	2021	34809	C0094651	Fleet	NFS asset Drayage	Lynwood	
4	4	2017-07-24	Monday	2017	4728	U0094376	Owner Operator	joes transportation	Norco	

---

1. Generate labels

In [7]:
```
# convert most_recent_load_date from string to timestamp
raw_df['most_recent_load_date'] = pd.to_datetime(raw_df['most_recent_load_date'])
```

In [8]:
```
# set 75th percentile threshold
most_recent_load_date_threshold = raw_df.most_recent_load_date.quantile(0.75)
total_loads_threshold = raw_df.total_loads.quantile(0.75)
```

In [9]:
```
# label drivers in the 75th percentile of 'loads' and 'most_recent_load_date' are assigned a label of 1
raw_df['label'] = (raw_df['most_recent_load_date'] >= most_recent_load_date_threshold) & (raw_df['total_loads']
raw_df["label"] = raw_df["label"].astype(int)
raw_df['label'].value_counts()
```

Out[9]:
```
0    73021
1    10393
Name: label, dtype: int64
```

In [10]:
```
rows_to_drop = 40000
query = raw_df.query("label==0")
if len(query) >= rows_to_drop:
  df_to_drop = query.sample(n=rows_to_drop, random_state=42)
  raw_df = raw_df.drop(df_to_drop.index)
```

In [11]:
```
raw_df['label'].value_counts()
```

Out[11]:
```
0    33021
1    10393
Name: label, dtype: int64
```

---

2. Drop total_loads and 'most_recent_load_date' from your data frame

---

In [12]:
```
df = raw_df.drop(['total_loads', 'most_recent_load_date'], axis=1)
df.head()
```

Out[12]:

	Unnamed: 0	dt	weekday	year	id_driver	id_carrier_number	dim_carrier_type	dim_carrier_company_name	home_base_city	ho
0	0	2019-12-16	Monday	2019	21350	U0109015	Owner Operator	CA&F TRUCKING	Maywood	
3	3	2021-02-10	Wednesday	2021	34809	C0094651	Fleet	NFS asset Drayage	Lynwood	

	Unnamed: 0	dt	weekday	year	id_driver	id_carrier_number	dim_carrier_type	dim_carrier_company_name	home_base_city	ho
6	6	2019-08-26	Monday	2019	15945	U0103984	Owner Operator	felipe gomez carranza	Ontario	
9	9	2021-02-01	Monday	2021	34503	C0094651	Fleet	NFS asset Drayage	Lynwood	
14	14	2020-07-30	Thursday	2020	34784	C0097561	Fleet	ADC TRANSPORT INC	Paramount	

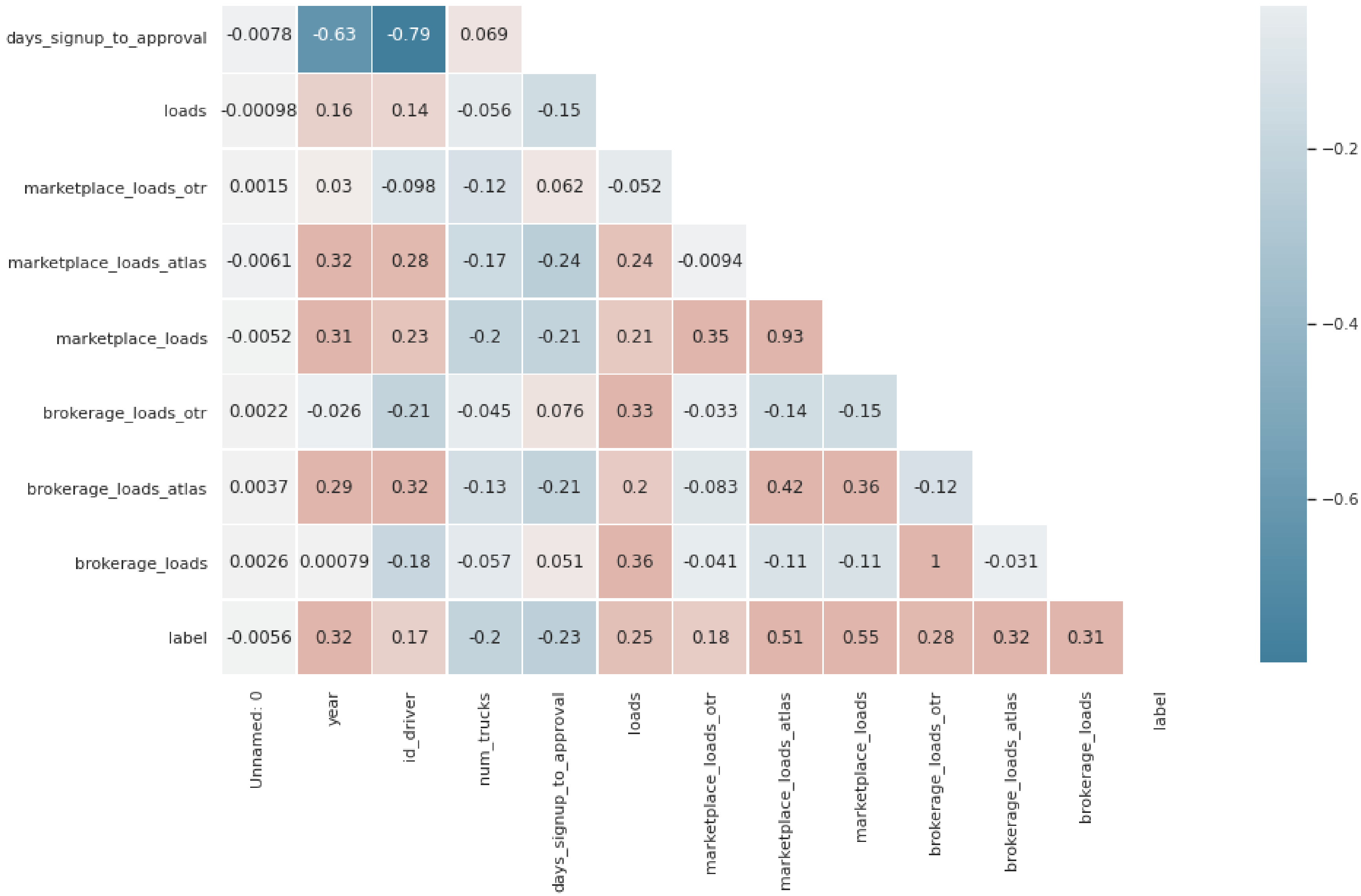
---

3. Run some basic statistics on your variables including correlations with labels and report findings

---

In [13]:

```
import matplotlib.transforms
import seaborn as sns

sns.set(style="white")
corr = df.corr()

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f,ax = plt.subplots(figsize=(15,15))

cmap = sns.diverging_palette(230,20,as_cmap=True)
sns.heatmap(corr, annot=True, mask=mask, cmap=cmap, vmax=.3, center=0, square=True, linewidths=.5, cbar_kws={"s

plt.yticks(rotation = 0)
plt.show()
```



From the correlation graphs above, we are able to find that there is a strong negative correlation between days_signup_to_approval and year. Also, there is a positive coorelation between `marketplace_loads` and `marketplace_loads_atlas` , `brokerage_loads` and `brokerage_loads_otr` .

In [14]:
```
df.describe()
```

Out[14]:

	Unnamed: 0	year	id_driver	num_trucks	days_signup_to_approval	loads	marketplace_loads_otr	marl

	Unnamed: 0	year	id_driver	num_trucks	days_signup_to_approval	loads	marketplace_loads_otr	marl
count	43414.000000	43414.000000	43414.000000	43385.000000	37223.000000	43414.000000	43414.000000	
mean	41661.775602	2019.083568	18801.902981	19.910130	273.267066	2.287741	33.946538	
std	24131.267913	1.325277	11547.705496	45.857461	381.792615	2.997736	94.063826	
min	0.000000	2015.000000	20.000000	1.000000	0.000000	1.000000	0.000000	
25%	20718.250000	2018.000000	8985.000000	1.000000	0.000000	1.000000	0.000000	
50%	41622.000000	2019.000000	17716.000000	2.000000	18.000000	1.000000	2.000000	
75%	62708.750000	2020.000000	29477.500000	11.000000	439.500000	3.000000	24.000000	
max	83413.000000	2021.000000	38096.000000	195.000000	1653.000000	102.000000	902.000000	

---

4. Create a data feature extraction plan and implement a pipeline to execute it

---

In [15]:

```
df.head()
```

Out[15]:

	Unnamed: 0	dt	weekday	year	id_driver	id_carrier_number	dim_carrier_type	dim_carrier_company_name	home_base_city	hor
0	0	2019-12-16	Monday	2019	21350	U0109015	Owner Operator	CA&F TRUCKING	Maywood	
3	3	2021-02-10	Wednesday	2021	34809	C0094651	Fleet	NFS asset Drayage	Lynwood	
6	6	2019-08-26	Monday	2019	15945	U0103984	Owner Operator	felipe gomez carranza	Ontario	
9	9	2021-02-01	Monday	2021	34503	C0094651	Fleet	NFS asset Drayage	Lynwood	
14	14	2020-07-30	Thursday	2020	34784	C0097561	Fleet	ADC TRANSPORT INC	Paramount	

In [16]:

```
df.nunique()
```

Out[16]:

```
Unnamed: 0                    43414
dt                             1853
weekday                           7
```

```
year                           7
id_driver                   4005
id_carrier_number           2011
dim_carrier_type               2
dim_carrier_company_name    1945
home_base_city               397
home_base_state               38
carrier_trucks                15
num_trucks                    30
interested_in_drayage          2
port_qualified                 2
signup_source                  2
ts_signup                   2011
ts_first_approved           1499
days_signup_to_approval      572
driver_with_twic               2
dim_preferred_lanes           41
first_load_date             1357
load_day                    1853
loads                         62
marketplace_loads_otr        108
marketplace_loads_atlas      196
marketplace_loads            228
brokerage_loads_otr          216
brokerage_loads_atlas        101
brokerage_loads              241
label                          2
dtype: int64
```

In [17]:
```
features_dropped = ['Unnamed: 0', "dt", "weekday",  "year", "id_driver",
                    "id_carrier_number", 'dim_carrier_company_name',
                    'ts_signup', 'ts_first_approved', 'first_load_date',
                    'load_day', 'days_signup_to_approval',
                    'dim_preferred_lanes', 'home_base_city']
categorical_features = ['dim_carrier_type', 'driver_with_twic', 'home_base_state',
                        'carrier_trucks', 'interested_in_drayage', 'port_qualified',
                        'signup_source']
numerical_features = ['num_trucks',
                      'loads', 'marketplace_loads_otr', 'marketplace_loads_atlas',
                      'marketplace_loads', 'brokerage_loads_otr',
                      'brokerage_loads_atlas', 'brokerage_loads', 'loads_per_truck']
```

In [18]:
```
other_home_base_state = 'home_base_state_not_indicated'
# other_home_base_city = 'home_base_city_not_indicated'

df['home_base_state'].fillna(other_home_base_state, inplace=True)
# df['home_base_city'].fillna(other_home_base_city, inplace=True)
```

```
df['num_trucks'].fillna(1, inplace=True)
```

In [19]:

```
# Augment Features
df["loads_per_truck"] = df["loads"]/df["num_trucks"]
```

In [20]:

```
dropped_df = df.drop(features_dropped, axis=1)
dropped_df.isnull().sum()
```

Out[20]:

```
dim_carrier_type            0
home_base_state             0
carrier_trucks              0
num_trucks                  0
interested_in_drayage       0
port_qualified              0
signup_source               0
driver_with_twic            0
loads                       0
marketplace_loads_otr       0
marketplace_loads_atlas     0
marketplace_loads           0
brokerage_loads_otr         0
brokerage_loads_atlas       0
brokerage_loads             0
label                       0
loads_per_truck             0
dtype: int64
```

In [21]:

```
df_y = dropped_df['label'].copy()
df_x = dropped_df.drop('label', axis=1)
df_x.shape, df_y.shape
```

Out[21]:

```
((43414, 16), (43414,))
```

In [22]:

```
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.base import BaseEstimator, TransformerMixin

num_pipeline = Pipeline([
        ('std_scaler', StandardScaler()),
  ])
```

```
full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numerical_features),
        ("cat", OneHotEncoder(), categorical_features),
])
```

In [23]:
```
train_prepared = full_pipeline.fit_transform(df_x)
train_prepared.shape
```

Out[23]: (43414, 73)

In [24]:
```
from sklearn.model_selection import train_test_split
df_y = dropped_df['label']
train_X, test_X, train_y, test_y = train_test_split(train_prepared, df_y, test_size=0.2, random_state=42)
train_X.shape, test_X.shape, train_y.shape, test_y.shape
```

Out[24]: ((34731, 73), (8683, 73), (34731,), (8683,))

In [25]:
```
type(train_y.to_numpy())
```

Out[25]: numpy.ndarray

In [26]:
```
type(train_X.toarray())
```

Out[26]: numpy.ndarray

---

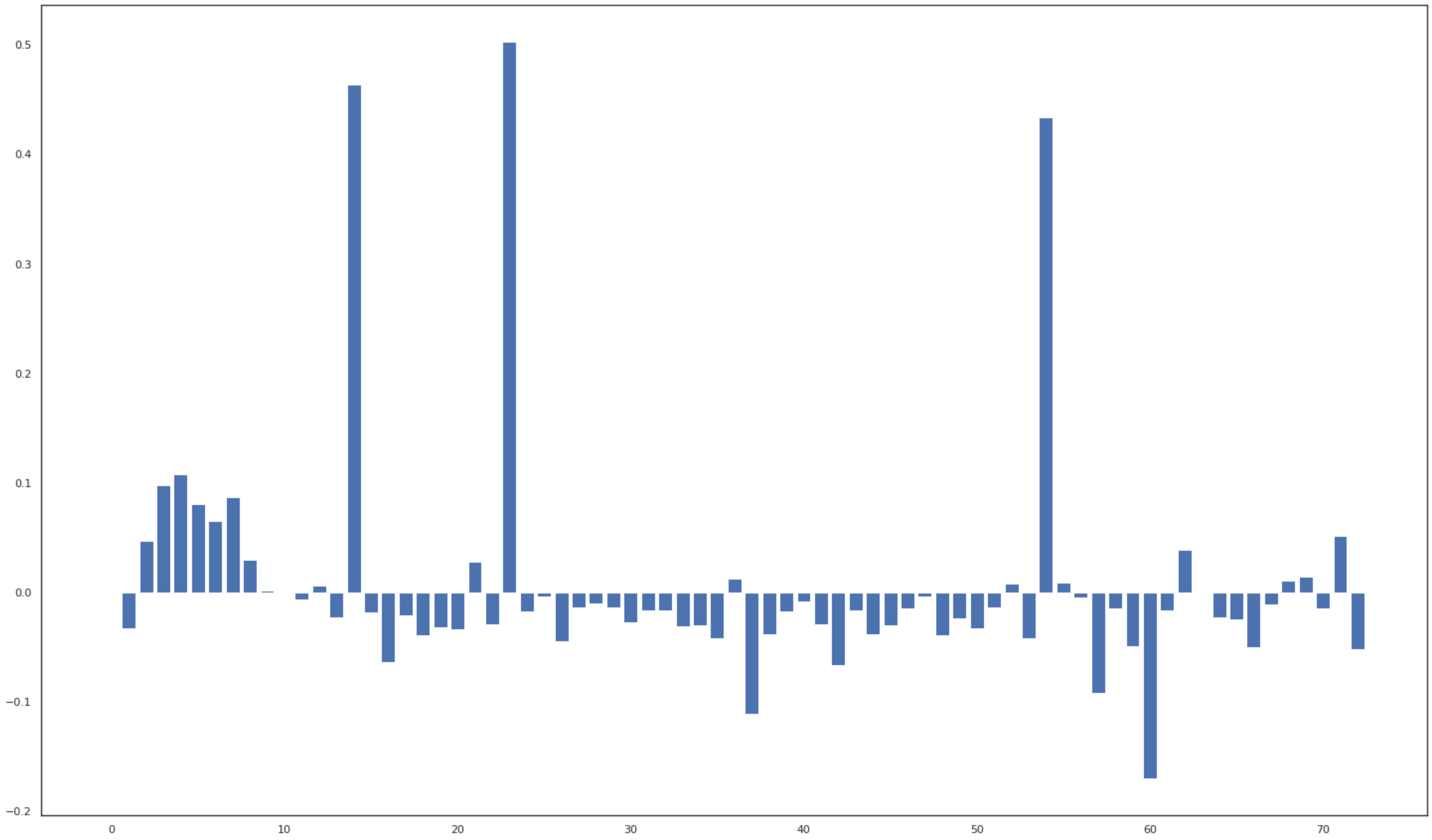
5. Implement a basic Linear Regression to find and interpret important features

---

In [27]:
```
from sklearn.datasets import make_regression
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
```

In [28]:
```
# Linear Regression Feature Importance
model = LinearRegression()
model.fit(train_X, train_y)
importance = model.coef_

# for i,v in enumerate(importance):
#          print('Feature: %0d, Score: %.5f' % (i,v))

plt.figure(figsize=(25, 15))
```

```
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

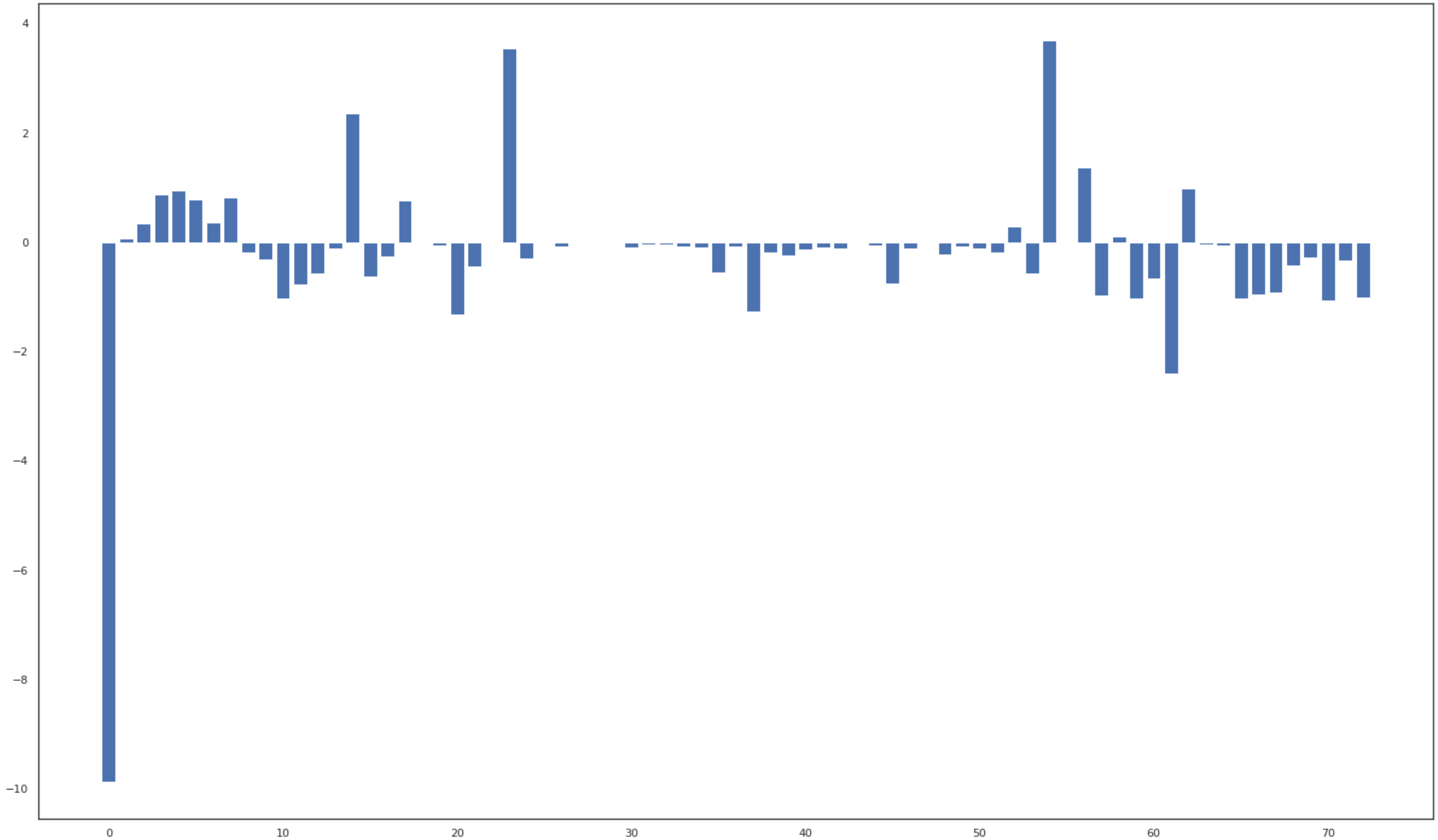


In [29]:

```
# Logistic Regression Feature Importance
model = LogisticRegression()
model.fit(train_X, train_y)
importance = model.coef_[0]

# for i,v in enumerate(importance):
#         print('Feature: %0d, Score: %.5f' % (i,v))

plt.figure(figsize=(25, 15))
```

```python
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```



6. Implement Principle Component Analysis (PCA)

In [30]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=10)
train_X_PCA = pca.fit_transform(train_X.toarray())
test_X_PCA = pca.fit_transform(test_X.toarray())
```

In [31]:
```
train_X_PCA.shape, test_X_PCA.shape
```

Out[31]:
```
((34731, 10), (8683, 10))
```

In [32]:
```
train_X_PCA
```

Out[32]:
```
array([[ 1.58997452e+00,  4.23276975e+00,  8.85648795e-02, ...,
         3.96968775e-02, -5.94580481e-01, -1.65385849e+00],
       [-1.27086914e+00, -6.74718550e-01,  3.00911874e-01, ...,
         7.63860527e-04,  1.04221454e-01, -9.96076978e-02],
       [ 3.08107751e+00,  2.60645356e-01, -1.62998780e+00, ...,
        -1.48831640e+00, -4.55421998e-01, -1.62474450e-01],
       ...,
       [ 3.72190071e+00,  5.73229362e-01, -6.71255984e-02, ...,
         1.35697909e-02, -2.44353884e-02,  5.09744623e-01],
       [ 3.29230585e+00,  7.06563824e-02, -4.40846345e-02, ...,
         4.41166355e-03,  1.13387302e-01,  6.31338682e-01],
       [ 2.06764139e+00, -4.50308461e-01, -1.04828475e+00, ...,
        -7.50748841e-01, -1.46969322e-01, -1.16356263e-01]])
```

In [33]:
```
print(pca.explained_variance_ratio_)
```

```
[0.28185906 0.18903636 0.12477708 0.09551251 0.08193667 0.05760123
 0.04223376 0.03684491 0.0206223  0.01426004]
```

---

7. Employ an ensemble method to your classification exercise

In [34]:
```
# For 9: Cross-Validate training results
# might want to add: (Optional: employ a stratifiedshufflesplit as well to ensure equitable distribution along
from sklearn.metrics import f1_score, make_scorer
from sklearn import model_selection
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
```

```
kfold = model_selection.KFold(n_splits=10)
num_trees = 100
bagging_clf = BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=num_trees, random_state=4
f1_scorer = make_scorer(f1_score)
results = model_selection.cross_val_score(bagging_clf, train_X_PCA, train_y, scoring=f1_scorer, cv=kfold)
print(results.mean())
```

```
0.9973647237245802
```

In [35]:

```
from sklearn.model_selection import GridSearchCV
param_grid = {
    'base_estimator__max_depth' : [1, 2, 3, 4, 5],
    'n_estimators' : [10, 100, 200]
}

bagging_clf = GridSearchCV(BaggingClassifier(DecisionTreeClassifier()), param_grid, scoring = f1_scorer, cv = 5
bagging_clf.fit(train_X_PCA, train_y)
y_bagging_pred = bagging_clf.predict(test_X_PCA)
print(bagging_clf.best_params_)
print(f1_score(test_y, y_bagging_pred))
```

```
{'base_estimator__max_depth': 5, 'n_estimators': 200}
0.7660020986358868
```

---

8. Develop a Neural Net classifier

In [36]:

```
X_train_nn_pca = train_X_PCA
y_train_nn = train_y.to_numpy()
X_test_nn_pca = test_X_PCA
y_test_nn = test_y.to_numpy()
```

In [46]:

```
from sklearn.metrics import f1_score
from sklearn.neural_network import MLPClassifier

nn_clf = MLPClassifier( hidden_layer_sizes=(5, 5, 5), activation='relu', solver='sgd',
                       learning_rate='constant', learning_rate_init=0.01,
                       alpha=0.0001, max_iter=300,
                       random_state=42)
nn_clf.fit(train_X, train_y)
y_pred = nn_clf.predict(test_X)
f1_score(test_y, y_pred)
```

Out[46]:

```
0.9701456890374971
```

In [51]:
```
nn_clf = MLPClassifier( hidden_layer_sizes=(5, 5, 5), activation='relu', solver='sgd',
                        learning_rate='adaptive', learning_rate_init=0.04,
                        alpha=0.001, max_iter=300,
                        random_state=42)
nn_clf.fit(train_X, train_y)
y_pred = nn_clf.predict(test_X)
print(f1_score(test_y, y_pred))
```

```
0.9792970630717381
```

In [48]:
```
nn_clf = MLPClassifier( hidden_layer_sizes=(5, 5, 5), activation='relu', solver='adam',
                        alpha=0.001, max_iter=300,
                        random_state=42)
nn_clf.fit(train_X, train_y)
y_pred = nn_clf.predict(test_X)
print(f1_score(test_y, y_pred))
```

```
0.969711423801574
```

In [39]:
```
nn_pca_clf = MLPClassifier( hidden_layer_sizes=(5, 5, 5), activation='relu', solver='sgd',
                        learning_rate='constant', learning_rate_init=0.01,
                        alpha=0.0001, max_iter=300,
                        random_state=42)
nn_pca_clf.fit(X_train_nn_pca, y_train_nn)
y_pred = nn_pca_clf.predict(X_test_nn_pca)
print(f1_score(y_test_nn, y_pred))
```

Out[39]:
```
0.7354368932038835
```

9. Cross-Validate training result

In [58]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedShuffleSplit
```

In [53]:
```
kfold = model_selection.KFold(n_splits=10)
num_trees = 100
bagging_clf = BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=num_trees, random_state=4
f1_scorer = make_scorer(f1_score)
```

In [54]:
```
#model for bagging classifier
results = cross_val_score(bagging_clf, train_X_PCA, train_y, scoring=f1_scorer, cv=kfold)
```

In [55]:
```
print(results)
print("Bagging classifier has %f accuracy with a standard deviation of %f" % (results.mean(), results.std()))
```

```
[0.9993921  0.99583581 0.99811912 0.99574985 0.99700419 0.99825885
 0.99827883 0.99764706 0.99697153 0.99638989]
Bagging classifier has 0.997365 accuracy with a standard deviation of 0.001121
```

In [56]:

```
# NN classifier
results = cross_val_score(nn_clf, train_X_PCA, train_y, scoring=f1_scorer, cv=kfold)
print(results)
print("NN classifier has %f accuracy with a standard deviation of %f" % (results.mean(), results.std()))
```

```
[0.91333333 0.93893557 0.93006993 0.9254902  0.91588785 0.94401756
 0.94302767 0.9256927  0.94447624 0.93386094]
NN classifier has 0.931479 accuracy with a standard deviation of 0.010791
```

In [59]:

```
#Bagging classifier with stratified shuffle split

cv = StratifiedShuffleSplit(n_splits=5, test_size=0.3, random_state=0)
results = cross_val_score(bagging_clf, train_X_PCA, train_y, scoring=f1_scorer, cv=cv)
print(results)
print("Bagging classifier has %f accuracy with a standard deviation of %f" % (results.mean(), results.std()))
```

```
[0.99541376 0.99640719 0.99701017 0.99482072 0.99621137]
Bagging classifier has 0.995973 accuracy with a standard deviation of 0.000770
```

In [60]:

```
# NN classifier with stratified shuffle split
results = cross_val_score(nn_clf, train_X_PCA, train_y, scoring=f1_scorer, cv=cv)
print(results)
print("NN classifier has %f accuracy with a standard deviation of %f" % (results.mean(), results.std()))
```

```
[0.9286905  0.93415638 0.94002999 0.93863764 0.93930311]
NN classifier has 0.936164 accuracy with a standard deviation of 0.004262
```