Predicting Automobile Insurance Claims

https://github.com/jaworXYZ/5509

Project Topic

The project looks at the utility of a LinearSVM versus two non-parametric classifiers (random forest and KNN) for predicting automobile insurance claims. With increased ability to predict the likelihood of claims, insurers could optimize premiums to increase profits or *ideally* reduce costs to customers less likely to have claims.

Data

This project is based off a dataset posted to Kaggle (https://www.kaggle.com/datasets/ifteshanajnin/carinsuranceclaimprediction-classification). The dataset consists of features relating to the policy holder (age, location, etc.) and features relating to the car itself. The dataset includes a binary label indicating whether or not the policy holder placed a claim within six months of the data point.

The data is contained in a single .csv file and translates to a dataframe of over 58,000 rows and a mix of roughly 15 numerical features and almost 30 categorical features.

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

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
from sklearn.metrics import f1_score
#from sklearn.model_selection import cross_val_score, GridSearchCV

import matplotlib.pylab as plt
%matplotlib inline

pd.options.display.max_columns = 200
```

In [2]:
```
df = pd.read_csv('data/train.csv')
print(df.shape)
```

```
(58592, 44)
```

In [3]:
```
df.head(3)
```

Out[3]:

	policy_id	policy_tenure	age_of_car	age_of_policyholder	area_cluster	population_density	make	segment	mo
0	ID00001	0.515874	0.05	0.644231	C1	4990	1	A	
1	ID00002	0.672619	0.02	0.375000	C2	27003	1	A	
2	ID00003	0.841110	0.02	0.384615	C3	4076	1	A	

The dataset is composed of both numerical and categorical data. The data includes an index column (which I will remove), 42 features, and binary label. Now divide the df into X and y:

In [4]:
```
X = df.iloc[:,1:-1]
X.shape
```

Out[4]:
```
(58592, 42)
```

In [5]:
```
y = df.iloc[:,-1]
y.shape
```

Out[5]:
```
(58592,)
```

Data Cleaning & Exploratory Data Analysis

In [6]:
```
X.describe()
```

Out[6]:

	policy_tenure	age_of_car	age_of_policyholder	population_density	make	airbags	displacen
count	58592.000000	58592.000000	58592.000000	58592.000000	58592.000000	58592.000000	58592.00(
mean	0.611246	0.069424	0.469420	18826.858667	1.763722	3.137066	1162.35!
std	0.414156	0.056721	0.122886	17660.174792	1.136988	1.832641	266.30⁄
min	0.002735	0.000000	0.288462	290.000000	1.000000	1.000000	796.00(
25%	0.210250	0.020000	0.365385	6112.000000	1.000000	2.000000	796.00(
50%	0.573792	0.060000	0.451923	8794.000000	1.000000	2.000000	1197.00(
75%	1.039104	0.110000	0.548077	27003.000000	3.000000	6.000000	1493.00(
max	1.396641	1.000000	1.000000	73430.000000	5.000000	6.000000	1498.00(

In [7]:
```
# "make" used a numerical datatype, but should be categorical
X['make'] = X['make'].astype('O')
```

In [8]:
```
# Previous description only included numerical features. Categorical features described here:
X.describe(exclude=np.number)
```

Out[8]:

	area_cluster	make	segment	model	fuel_type	max_torque	max_power	engine_type	is_es
count	58592	58592	58592	58592	58592	58592	58592	58592	5859
unique	22	5	6	11	3	9	9	11	
top	C8	1	B2	M1	Petrol	113Nm@4400rpm	88.50bhp@6000rpm	F8D Petrol Engine	N
freq	13654	38126	18314	14948	20532	17796	17796	14948	4019

In [9]:

```
# We will drop the features that are very unbalanced like "is_speed_alert" which is 99.4% yes
drop_list = ["is_speed_alert","is_power_steering","is_parking_sensors"]
X = X.drop(drop_list,axis=1)

# One-hot encode remaining categorical features to ensure better compatibility with Pandas and Sc
Xo = pd.get_dummies(X,drop_first=True)
```

```
C:\Users\jawor\anaconda3\lib\site-packages\pandas\core\algorithms.py:798: FutureWarning: In a fu
ture version, the Index constructor will not infer numeric dtypes when passed object-dtype seque
nces (matching Series behavior)
  uniques = Index(uniques)
```

In [10]:

```
Xo.shape
```

Out[10]:

```
(58592, 100)
```

Even dropping the (redundant) first columns of the categorical data, we now a very large set of features (100!).

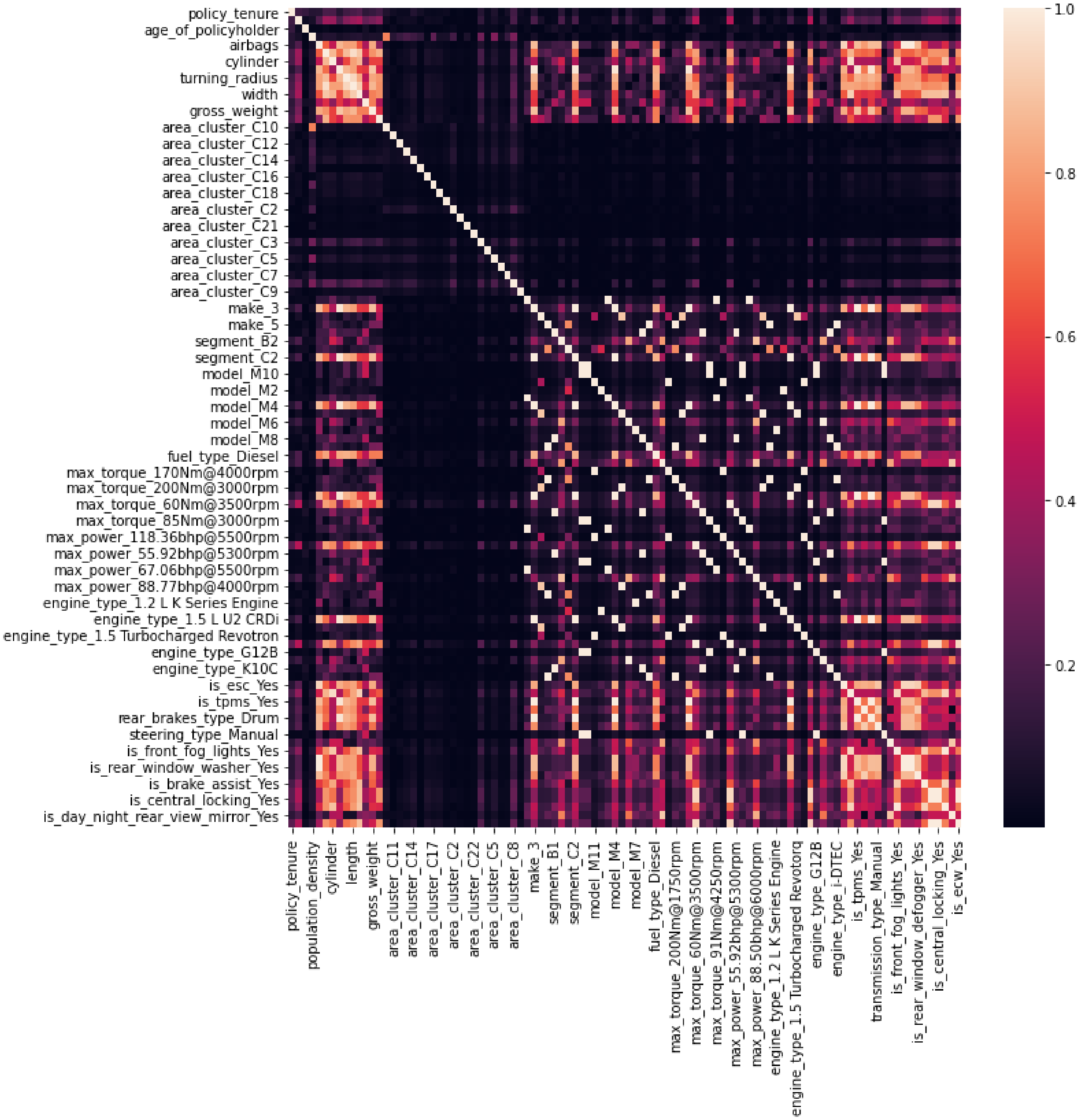
Now checking for correlation, and hopefully dropping some (many) columns:

In [11]:

```
corr = Xo.corr().abs()
fig, ax = plt.subplots(figsize=(11,11))          # Sample figsize in inches
sns.heatmap(corr,ax=ax)
```

Out[11]:

```
<AxesSubplot:>
```



There above heatmap shows that there are some points of very high correlation. However, with 100 features it isn't easy to see which features those are.

In [12]:
```
c = corr.abs().unstack().sort_values()
c[(c>0.9)&(c<1.0)]
```

Out[12]:
```
is_front_fog_lights_Yes           cylinder                            0.904696
cylinder                          is_front_fog_lights_Yes             0.904696
steering_type_Power               is_day_night_rear_view_mirror_Yes   0.905242
is_day_night_rear_view_mirror_Yes steering_type_Power                 0.905242
fuel_type_Petrol                  is_day_night_rear_view_mirror_Yes   0.910817
                                                                        ...
model_M4                          rear_brakes_type_Drum               1.000000
make_3                            rear_brakes_type_Drum               1.000000
rear_brakes_type_Drum             engine_type_1.5 L U2 CRDi           1.000000
                                  is_tpms_Yes                         1.000000
is_tpms_Yes                       rear_brakes_type_Drum               1.000000
Length: 86, dtype: float64
```

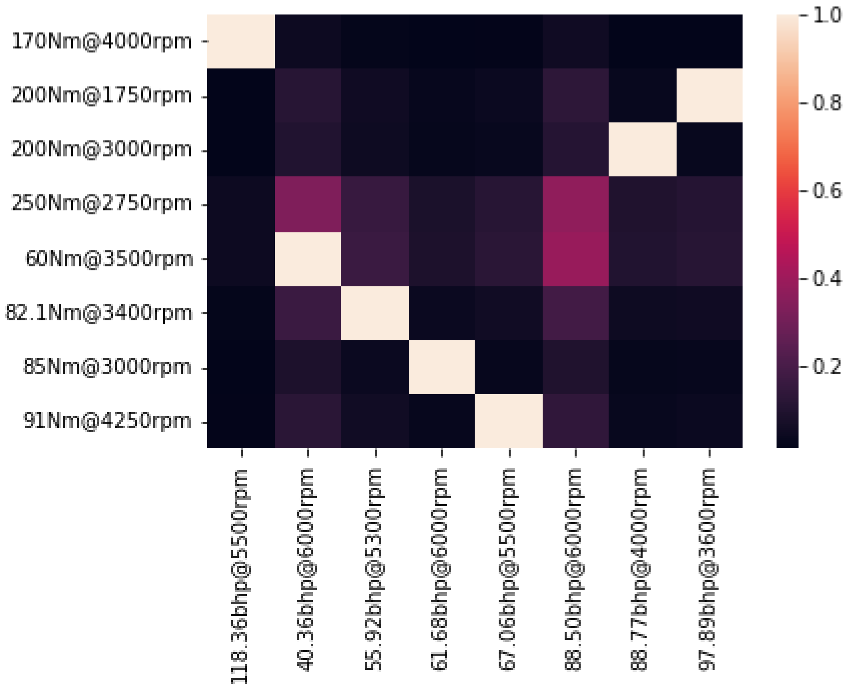
Accounting for duplicate pair, there are over 40 features with absolute correlation between 0 and 1. Rather than look at correlations between specific category labels, it seems sensible to compare categories themselves.

Next we will look at specific pairings of categoricals to see how they correlate, and see if they can be removed entirely.

In [13]:
```
# helper method to plot correlation of labels within specific features
def cat_corr(cat1,cat2):
    cat1o = pd.get_dummies(X[cat1],drop_first=True)
    cat2o = pd.get_dummies(X[cat2],drop_first=True)
    corr = cat1o.join(cat2o).corr().abs()
    corr = corr.iloc[cat1o.shape[1]:,:cat2o.shape[1]]
    print("Overall correlation is %s." % np.mean(corr.max()))
    sns.heatmap(corr)
```

In [14]:
```
cat_corr('max_power','max_torque')
```

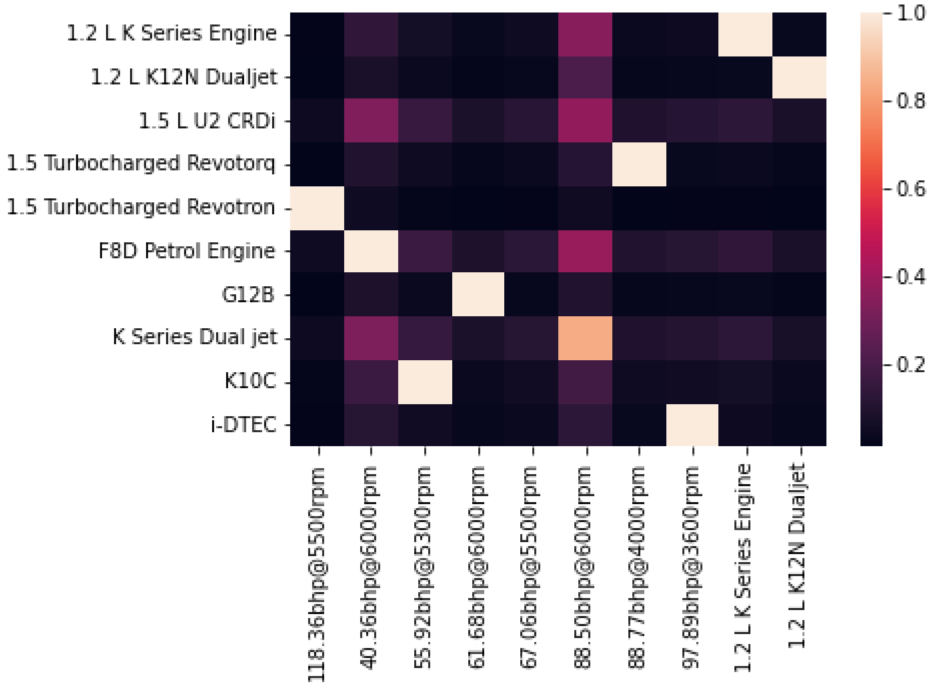
```
Overall correlation is 0.9233160799269159.
```



We can see that max power and torque are correlated almost 1:1 for almost all configurations and that the average correlation is above 90%. It would make sense to drop at least one of these features.

In [15]:
```
# continue checking other features
cat_corr('max_power','engine_type')
```

```
Overall correlation is 0.895968228162068.
```



Checking max_power against engine_type again confirms a strong correlation. This makes intuitive sense as there appear to be only a small handful of identical engine configurations.

Rather than analyze each pair individually, we should automate some of this:

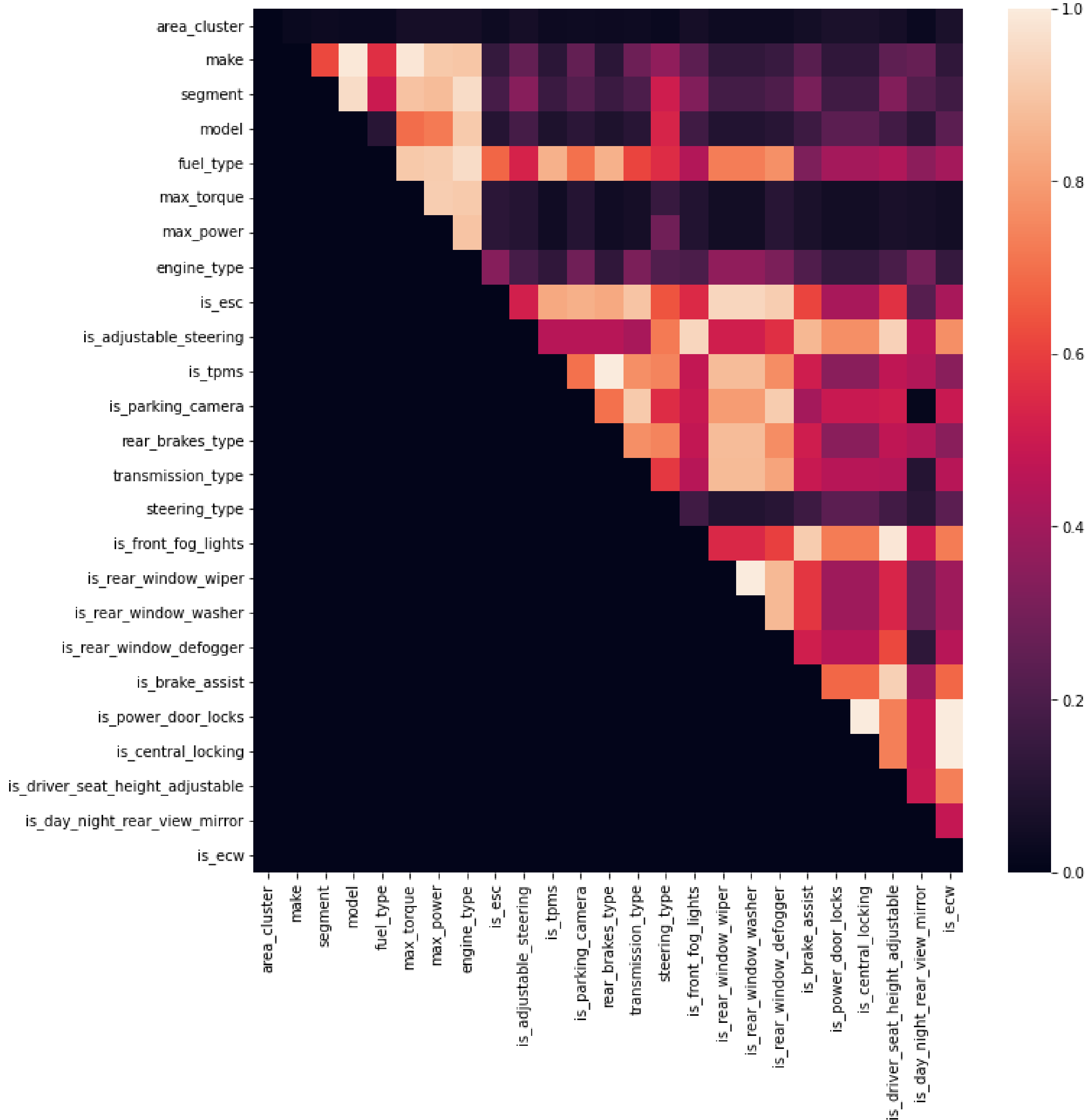
In [16]:
```
# create a list of categorical features
cat_list = []
for col in X.columns:
    if X[col].dtype == 'O':
        cat_list.append(col)

# iterate through list of features and create average categorical correlation plot for values ove
corr = []
for i in range(len(cat_list)):
    next_line = []
    for j in range(len(cat_list)):
        if i >= j:
            next_line.append(0)
        else:
            cat1o = pd.get_dummies(df[cat_list[i]],drop_first=True)
            cat2o = pd.get_dummies(df[cat_list[j]],drop_first=True)
            corr_ij = pd.concat([cat1o, cat2o], axis=1).corr().abs()
            corr_ij = corr_ij.iloc[cat1o.shape[1]:,:cat2o.shape[1]]
            next_line.append(np.mean(corr_ij.max()))
    corr.append(next_line)

corr = pd.DataFrame(corr,index=cat_list, columns=cat_list)

fig, ax = plt.subplots(figsize=(11,11))
sns.heatmap(corr,ax=ax)
```

Out[16]: <AxesSubplot:>



In [17]:

```
# identify most correlative categorical pairs
c = corr.unstack().sort_values()
c[(c>0.9)&(c<1.0)]
```

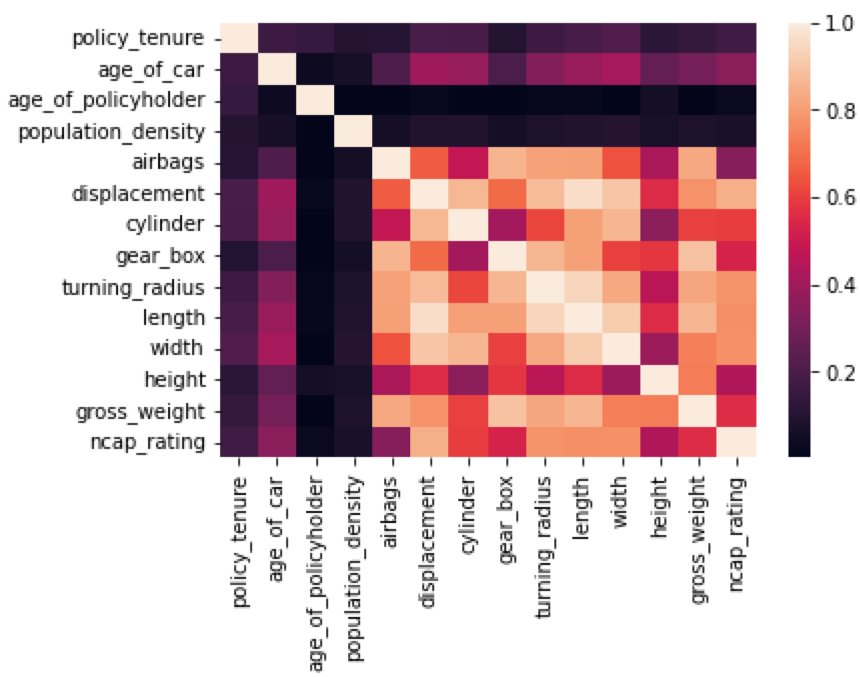
```
Out[17]: engine_type                        make                      0.902007
         max_power                          make                      0.908777
         max_torque                         fuel_type                 0.910149
         engine_type                        model                     0.912024
                                            max_torque                0.912024
         transmission_type                  is_parking_camera         0.913194
         is_brake_assist                    is_front_fog_lights       0.915803
         is_rear_window_defogger            is_parking_camera         0.916767
         max_power                          fuel_type                 0.916786
                                            max_torque                0.921298
         is_rear_window_defogger            is_esc                    0.921832
         is_driver_seat_height_adjustable   is_brake_assist           0.929115
                                            is_adjustable_steering    0.931436
         is_rear_window_wiper               is_esc                    0.943207
         is_rear_window_washer              is_esc                    0.943207
         is_front_fog_lights                is_adjustable_steering    0.945062
         model                              segment                   0.958323
         engine_type                        segment                   0.958323
                                            fuel_type                 0.960620
         is_driver_seat_height_adjustable   is_front_fog_lights       0.987346
         max_torque                         make                      0.987479
         model                              make                      0.989983
         rear_brakes_type                   is_tpms                   1.000000
         dtype: float64
```

```python
In [18]: # select categorical features from above pairs to reduce correlations within dataset
         # leaving 'make' in as I already want to drop many features it strongly correlates with
         drop_list = ['max_torque', 'max_power','model','is_tpms','is_front_fog_lights','fuel_type','is_r
```

Correlation of numerical features:

```python
In [19]: c2 = X.select_dtypes(exclude='O').corr().abs()
         sns.heatmap(c2)
```

```
Out[19]: <AxesSubplot:>
```




```python
In [20]: c2 = c2.unstack().sort_values()
         c2[(c2>0.9)&(c2<1.0)]
```

```
Out[20]: length          width            0.915918
         width           length           0.915918
         turning_radius  length           0.944899
         length          turning_radius   0.944899
                         displacement     0.961655
         displacement    length           0.961655
         dtype: float64
```

```
In [21]: # Add "length" to list of features to drop
         drop_list.append('length')
```

Create a reduced and normalized dataframe "Xn" to build models from

```
In [22]: # We will Xo now and create a new DataFrame with dropped features, one-hot encodings, and normal
         # Min-Max normalize numerical features to best fit with binary one-hot encodings of categorical 
         Xn = X.drop(drop_list,axis=1)
         for col in Xn.columns:
             if Xn[col].dtype != 'O':
                 #Xn[col] = (Xn[col]-Xn[col].mean())/Xn[col].std()
                 Xn[col] = (Xn[col]-Xn[col].min())/(Xn[col].max()-Xn[col].min())

         # OHE
         Xn = pd.get_dummies(Xn,drop_first=True)
         Xn
```

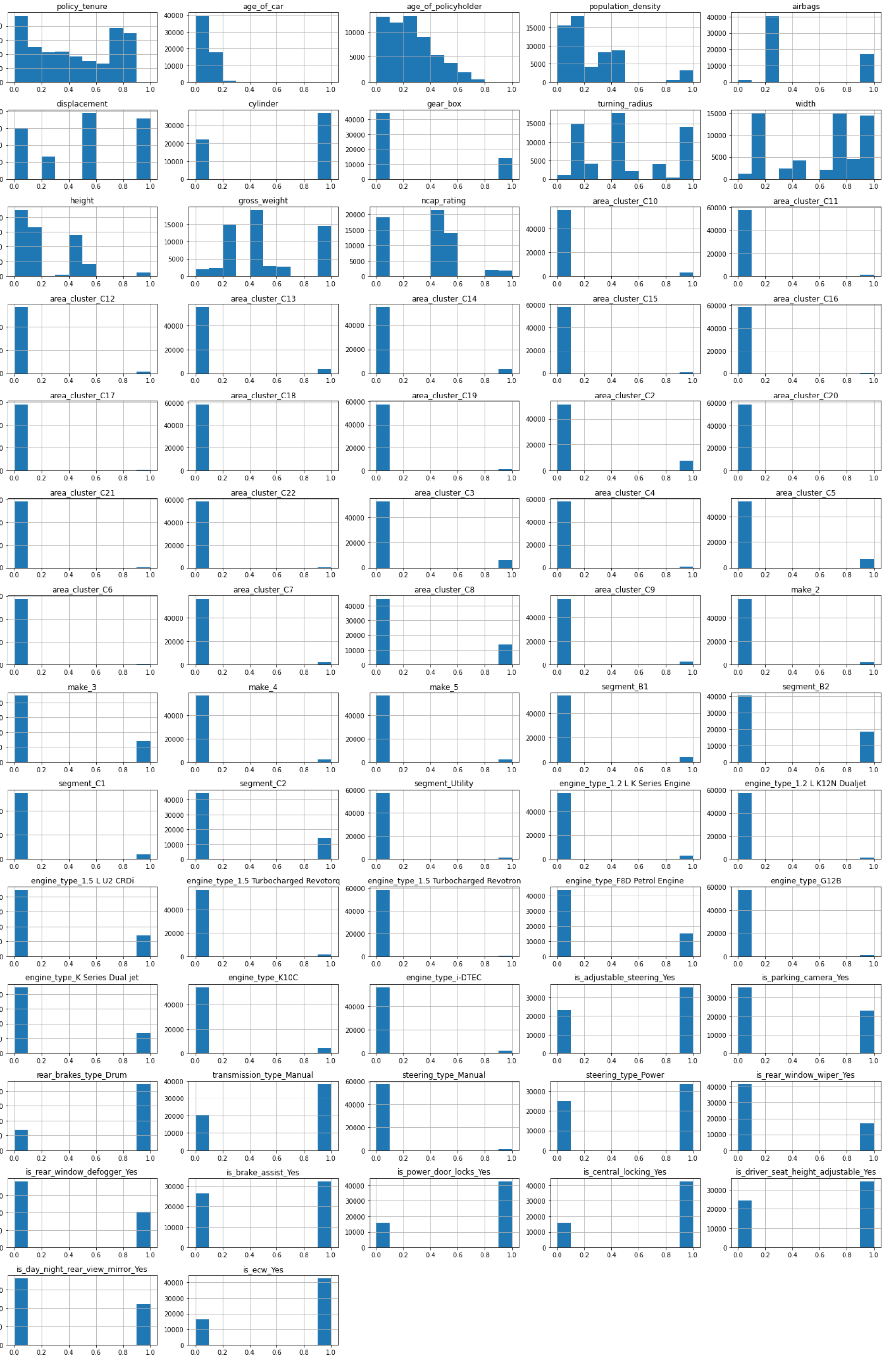
```
C:\Users\jawor\anaconda3\lib\site-packages\pandas\core\algorithms.py:798: FutureWarning: In a fu
ture version, the Index constructor will not infer numeric dtypes when passed object-dtype seque
nces (matching Series behavior)
  uniques = Index(uniques)
```

Out[22]:

	policy_tenure	age_of_car	age_of_policyholder	population_density	airbags	displacement	cylinder	gear_b
0	0.368130	0.05	0.500000	0.064260	0.2	0.000000	0.0	
1	0.480580	0.02	0.121622	0.365231	0.2	0.000000	0.0	
2	0.601457	0.02	0.135135	0.051764	0.2	0.000000	0.0	
3	0.643904	0.11	0.202703	0.291660	0.2	0.571225	1.0	
4	0.425902	0.11	0.486486	0.470987	0.2	0.289174	0.0	
...	...	...	...	...	...	...	...	
58587	0.252782	0.13	0.500000	0.116270	0.2	0.289174	0.0	
58588	0.858671	0.02	0.324324	0.102516	0.2	0.000000	0.0	
58589	0.831862	0.05	0.229730	0.470987	0.2	0.000000	0.0	
58590	0.884975	0.14	0.378378	0.116270	0.2	0.571225	1.0	
58591	0.087304	0.02	0.216216	0.116270	1.0	0.992877	1.0	

58592 rows × 67 columns

```
In [23]: Xn.hist(figsize=(20,30), layout=(14,5))
         plt.tight_layout()
```


policy_tenure
age_of_car
age_of_policyholder
population_density
airbags
displacement
cylinder
gear_box
turning_radius
width
height
gross_weight
ncap_rating
area_cluster_C10
area_cluster_C11
area_cluster_C12
area_cluster_C13
area_cluster_C14
area_cluster_C15
area_cluster_C16
area_cluster_C17
area_cluster_C18
area_cluster_C19
area_cluster_C2
area_cluster_C20
area_cluster_C21
area_cluster_C22
area_cluster_C3
area_cluster_C4
area_cluster_C5
area_cluster_C6
area_cluster_C7
area_cluster_C8
area_cluster_C9
make_2
make_3
make_4
make_5
segment_B1
segment_B2
segment_C1
segment_C2
segment_Utility
engine_type_1.2 L K Series Engine
engine_type_1.2 L K12N Dualjet
engine_type_1.5 L U2 CRDi
engine_type_1.5 Turbocharged Revotorq
engine_type_1.5 Turbocharged Revotron
engine_type_F8D Petrol Engine
engine_type_G12B
engine_type_K Series Dual jet
engine_type_K10C
engine_type_i-DTEC
is_adjustable_steering_Yes
is_parking_camera_Yes
rear_brakes_type_Drum
transmission_type_Manual
steering_type_Manual
steering_type_Power
is_rear_window_wiper_Yes
is_rear_window_defogger_Yes
is_brake_assist_Yes
is_power_door_locks_Yes
is_central_locking_Yes
is_driver_seat_height_adjustable_Yes
is_day_night_rear_view_mirror_Yes
is_ecw_Yes

The histograms of the numerical models don't suggest any irregularities in the data. The histograms of the categorical values don't illustrate very much other than which specific categories are under/over-presented within their features.

Split data into training and test sets:

In [24]:
```
X_train, X_test, y_train, y_test = train_test_split(Xn,y, test_size=0.15, random_state=13)
```

In [25]:
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(49803, 67)
(8789, 67)
(49803,)
(8789,)
```

Models & Results

In [26]:
```
# Check for imbalance among y values
np.mean(y_train)
```

Out[26]:
```
0.0647350561211172
```

Given the there are so few claims made (<6.5% of policies has claims), the data is quite imbalanced. Simple accuracy won't be sufficient for testing performance. Instead use the **F1-score**.

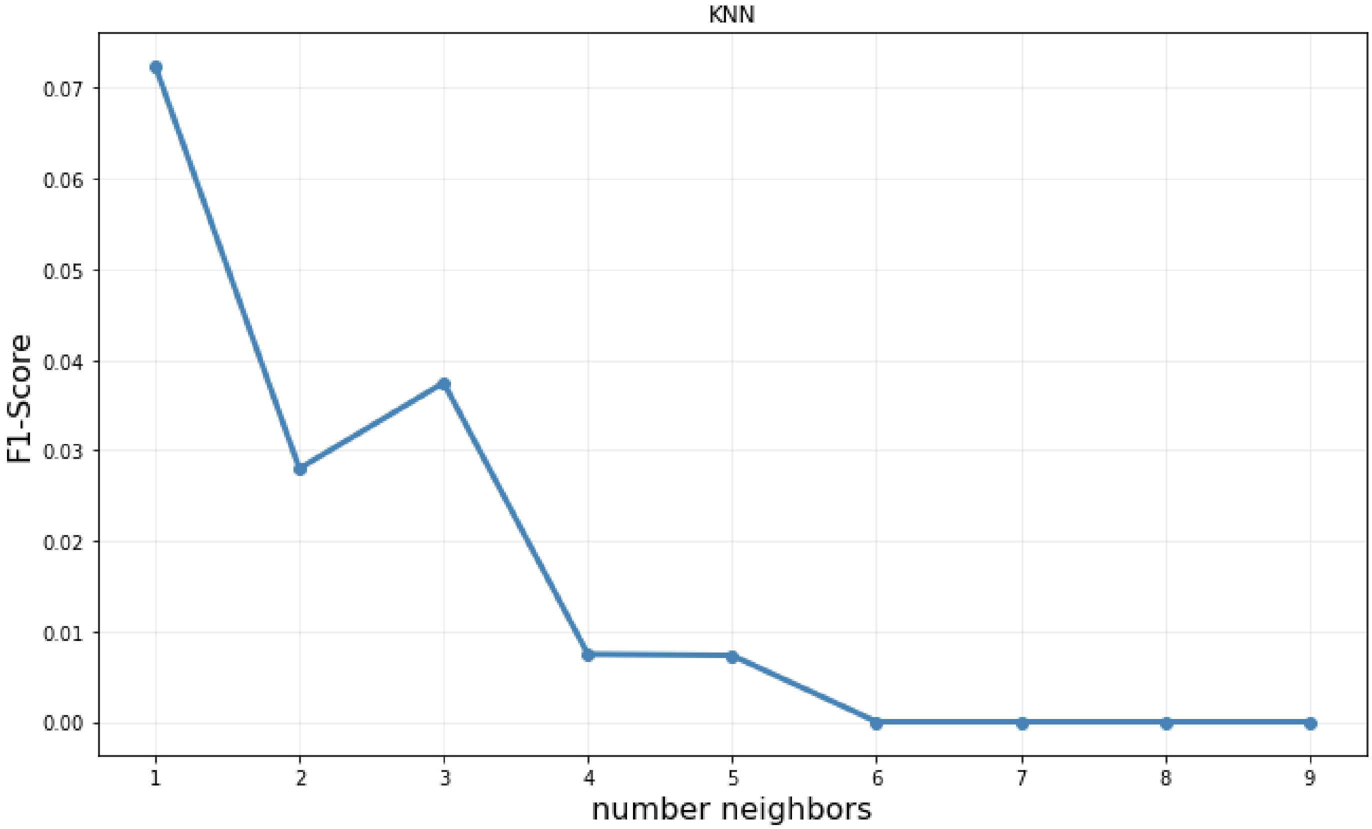
The imbalance will have to be accounted for in the models. It won't affect the KNN model, but the Random Forest in particular could be susceptible to issues with imbalance. The SKLearn implementations of both Random Forest and LinearSVC include class_weight parameters that will hopefully make a difference.

Model 1: KNN

In [27]:
```
# KNN for values of n_neighbors
all_par = range(1,10)
scores = []
for p in all_par:
    knn = KNeighborsClassifier(n_neighbors=p)
    y_hat = knn.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("number neighbors", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("KNN")
ax.grid(alpha=0.25)
```

```
Maximum F1-score of  0.0724907063197026
```



It is clear from the above that k=1 yields the highest performance. Unfortunately, the f-score is still very low. The is nothing to be done here to account for imbalance.

Model 2: Random Forest

We will begin with a default random forest and then modify some of the parameters to see what effect that has.

In [28]:
```
# RandomForest (Default)
y_hat = RandomForestClassifier(random_state=13).fit(X_train, y_train).predict(X_test)
f1_score(y_test,y_hat)
```

Out[28]: 0.013961605584642234

In [29]:
```
y_hat = RandomForestClassifier(max_features='log2',random_state=13).fit(X_train, y_train).predic
f1_score(y_test,y_hat)
```

Out[29]: 0.013937282229965157

In [30]:
```
y_hat = RandomForestClassifier(class_weight={0: 1, 1: 5},random_state=13).fit(X_train, y_train).
f1_score(y_test,y_hat)
```

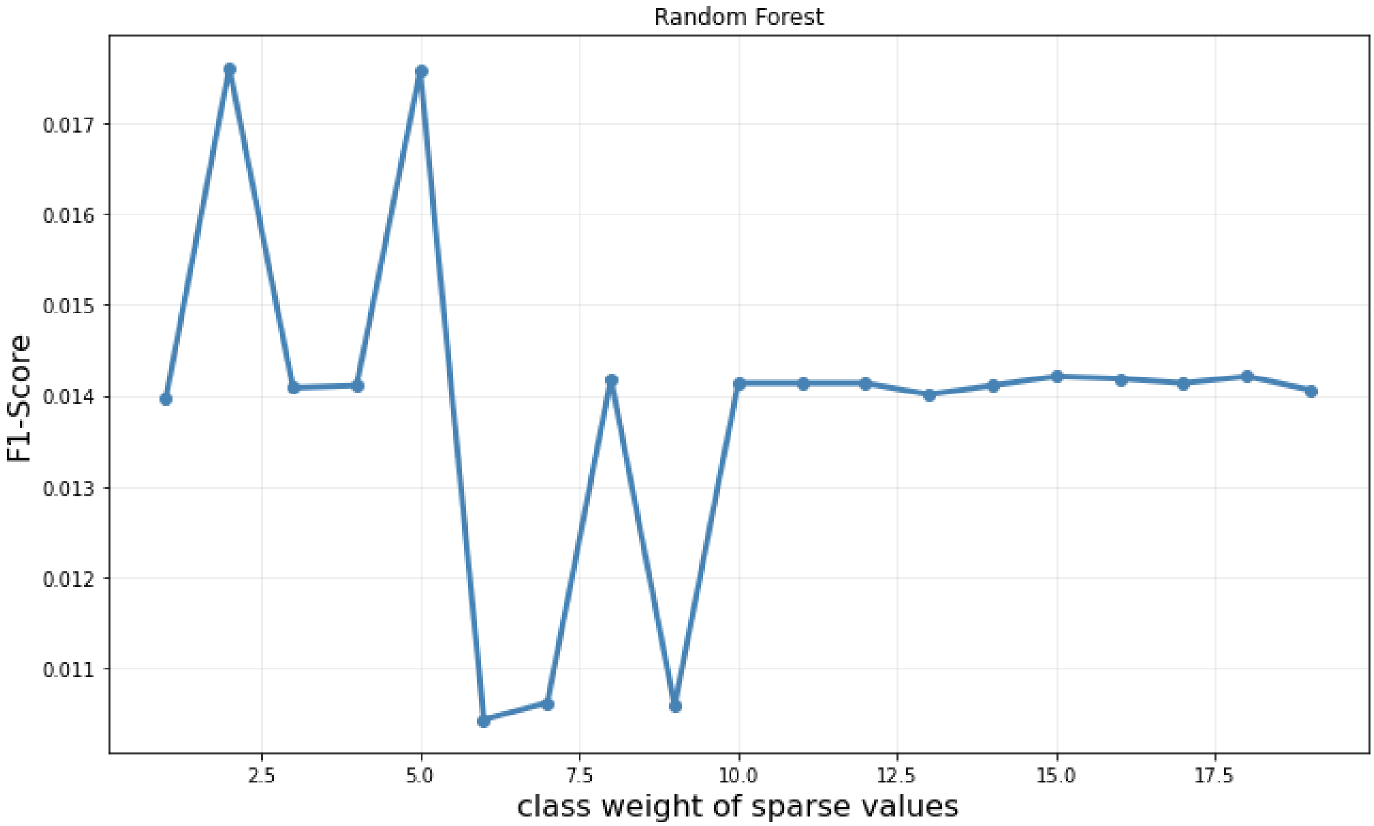
Out[30]: 0.017574692442882248

There is some promise here that increasing the class weights could lead to better performance.

In [31]:
```
# RandomForest for class_weights
all_par = range(1,20)
scores = []
for p in all_par:
    clf = RandomForestClassifier(class_weight={0: 1, 1: p},random_state=13)
    y_hat = clf.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))
```

```
print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("class weight of sparse values", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("Random Forest")
ax.grid(alpha=0.25)
```

```
Maximum F1-score of  0.017605633802816902
```

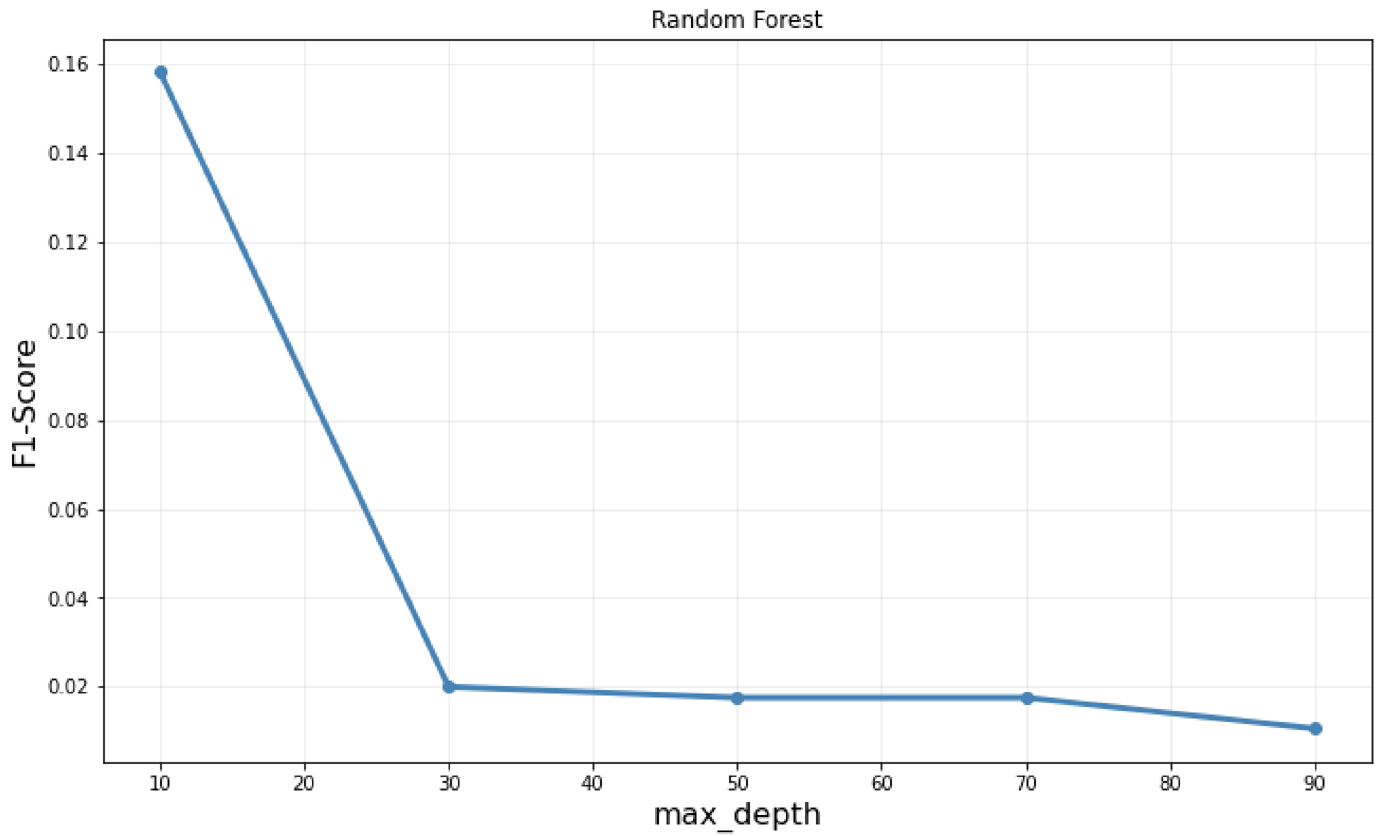


Given the jagged nature of the trendline, it doesn't appear that this will consistently improve the performance for any values of the class weight.

In [32]:
```
# RandomForest for values of max_depth
all_par = range(10,100,20)
scores = []
for p in all_par:
    clf = RandomForestClassifier(class_weight='balanced',max_depth=p)
    y_hat = clf.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("max_depth", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("Random Forest")
ax.grid(alpha=0.25)
```

```
Maximum F1-score of  0.15828877005347594
```

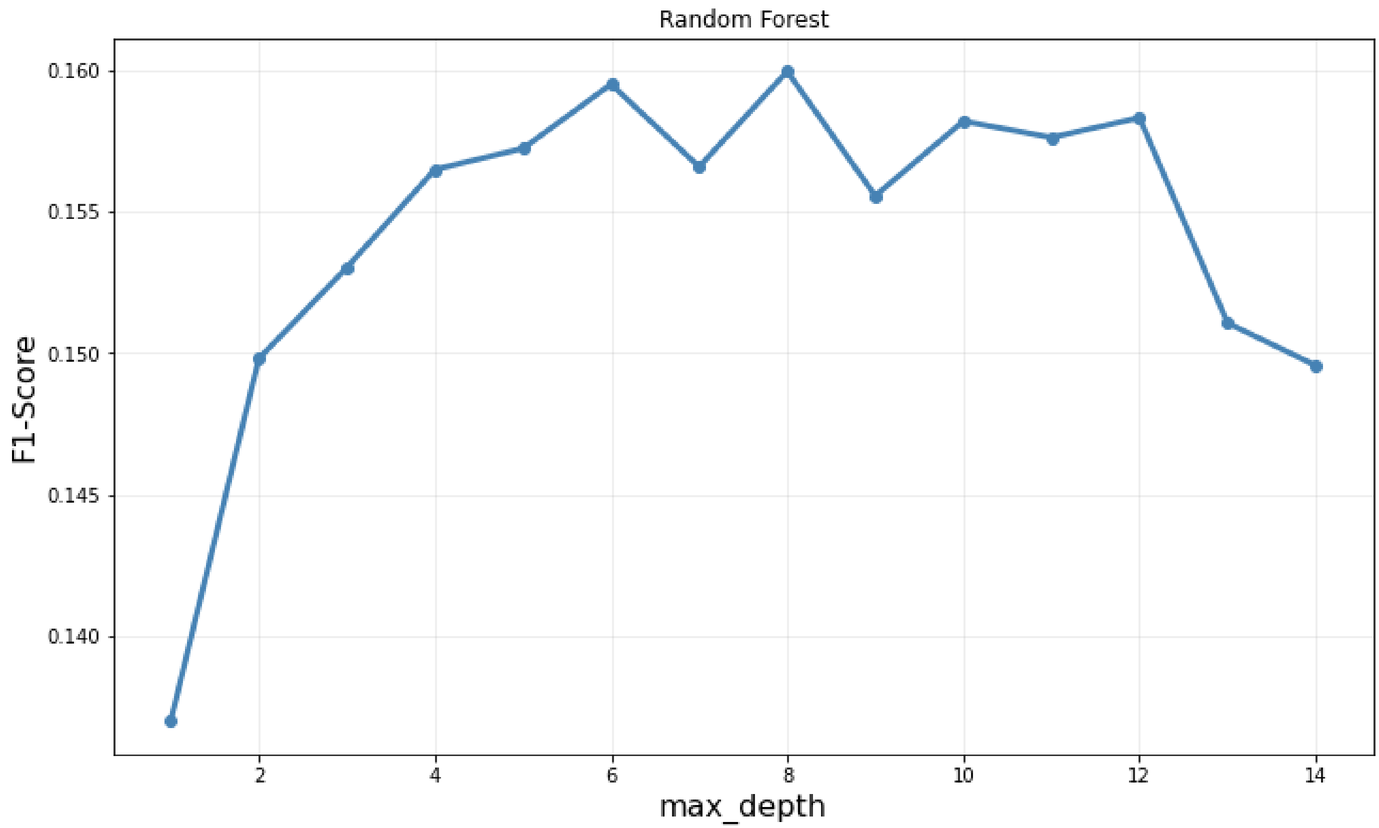


In [33]:

```
# RandomForest for values of max_depth (refined range of values)
all_par = range(1,15)
scores = []
for p in all_par:
    clf = RandomForestClassifier(class_weight='balanced',max_depth=p)
    y_hat = clf.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("max_depth", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("Random Forest")
ax.grid(alpha=0.25)
```

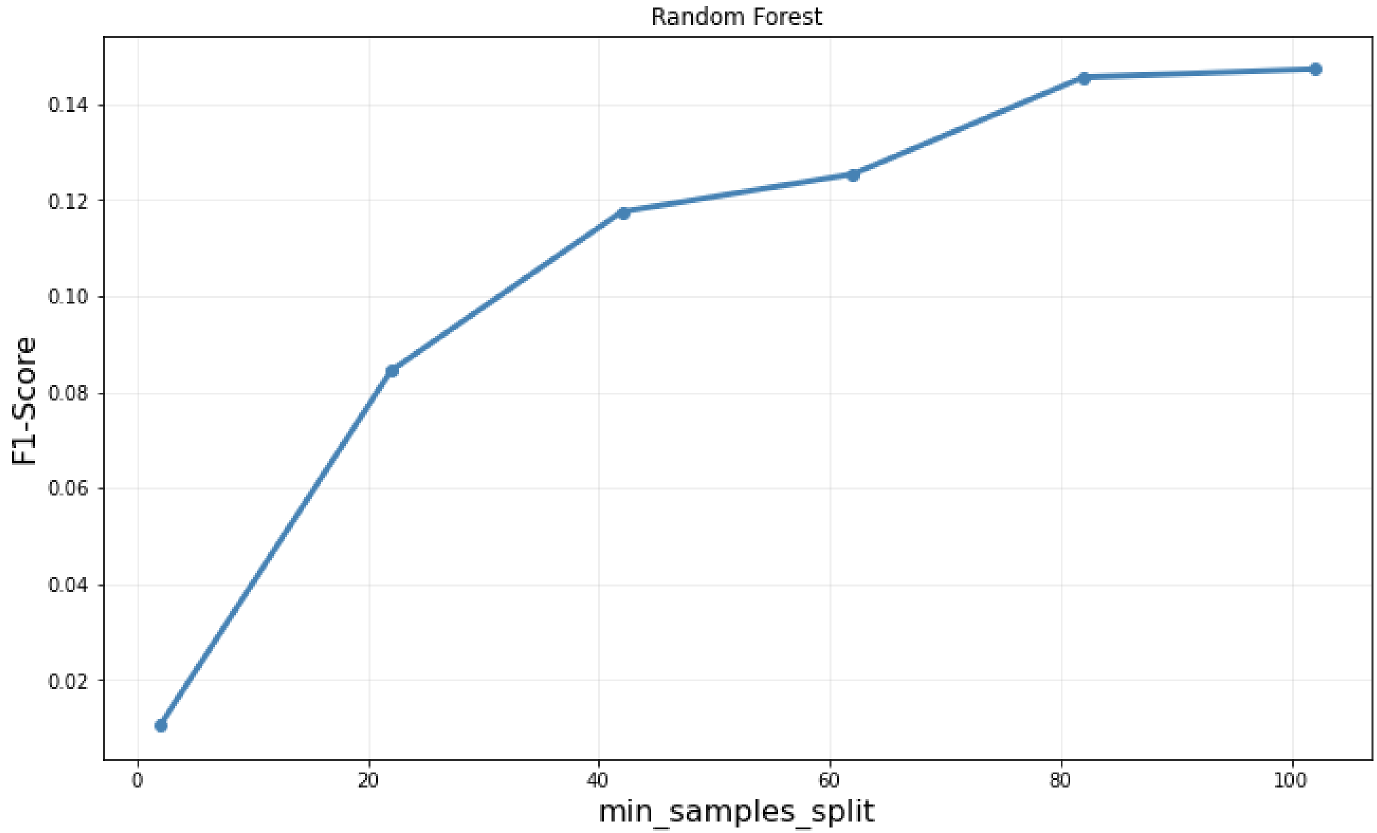
```
Maximum F1-score of  0.15998101115594587
```



In [34]:
```
# RandomForest for values of min_samples_split
all_par = range(2,122,20)
scores = []
for p in all_par:
    clf = RandomForestClassifier(class_weight='balanced',min_samples_split=p)
    y_hat = clf.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("min_samples_split", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("Random Forest")
ax.grid(alpha=0.25)
```

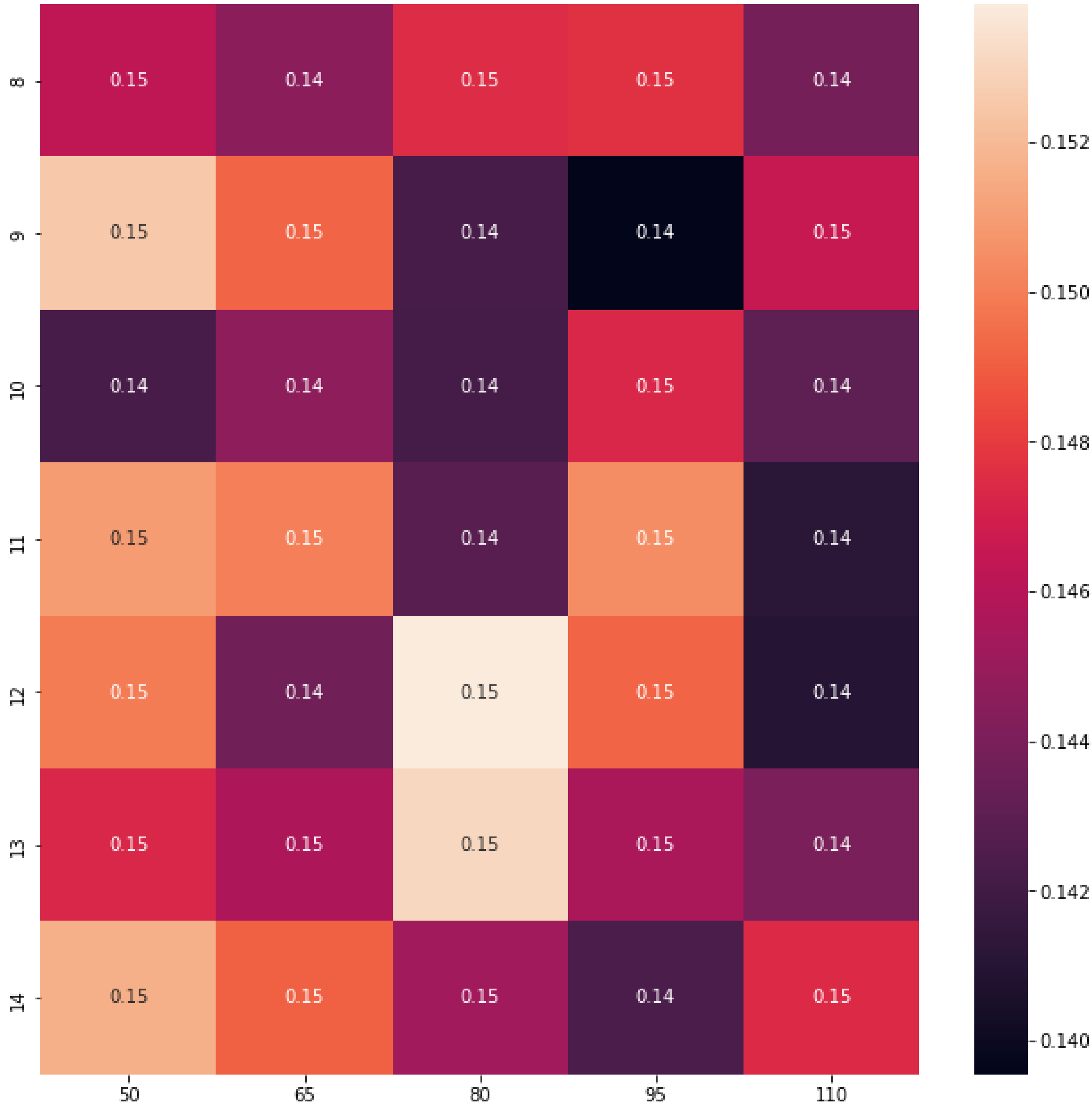
```
Maximum F1-score of  0.1472837022132797
```



In [35]:
```
# RandomForest grid search
all_max_depths = range(8,15)
all_min_split = range(50,125,15)
scores = []
for i in all_max_depths:
    next_line = []
    for j in all_min_split:
        clf = RandomForestClassifier(class_weight='balanced',min_samples_split=p)
        y_hat = clf.fit(X_train, y_train).predict(X_test)
        next_line.append(f1_score(y_test,y_hat))
    scores.append(next_line)
```

In [36]:
```
scores = pd.DataFrame(scores,index=all_max_depths, columns=all_min_split)
fig, ax = plt.subplots(figsize=(11,11))
sns.heatmap(scores,ax=ax,annot=True)
```

Out[36]:
```
<AxesSubplot:>
```

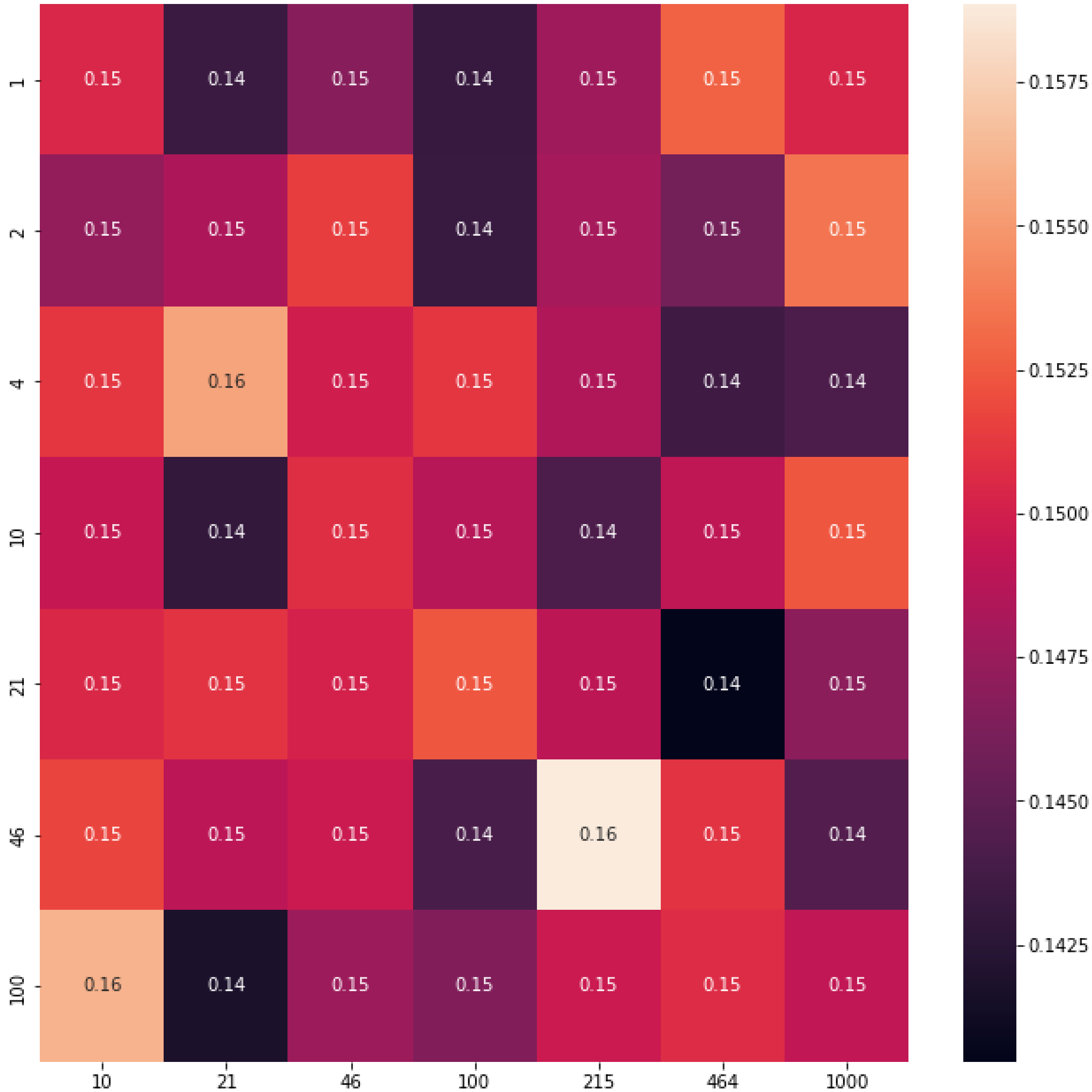


In [37]:

```
# RandomForest grid search over a larger range of values
all_max_depths = np.logspace(0,2,7).astype(int)
all_min_split = np.logspace(1,3,7).astype(int)
scores = []
for i in all_max_depths:
    next_line = []
    for j in all_min_split:
        clf = RandomForestClassifier(class_weight='balanced',min_samples_split=p)
        y_hat = clf.fit(X_train, y_train).predict(X_test)
        next_line.append(f1_score(y_test,y_hat))
    scores.append(next_line)

scores = pd.DataFrame(scores,index=all_max_depths, columns=all_min_split)
fig, ax = plt.subplots(figsize=(11,11))
sns.heatmap(scores,ax=ax,annot=True)
```

Out[37]: <AxesSubplot:>



It doesn't appear likely that any combination of values will result in performance exceeding the earlier max F1-score of 0.162 when using max_depth=11

Model 3: Linear SVC

Begin with default model.

In [38]:
```
# LinearSVC (Default)
y_hat = LinearSVC(random_state=13).fit(X_train, y_train).predict(X_test)
f1_score(y_test,y_hat)
```

Out[38]:
```
0.0
```

In [39]:
```
y_hat.mean()
```

Out[39]:
```
0.0
```

The default model has F1-score of zero, which suggests either the precision or accuracy are zero. Checking the mean shows that model is mislabeling everything as "0" (no claim). This is likely due to the lack of imbalance handling.

In [40]:

```
# LinearSVC (Balanced)
y_hat = LinearSVC(random_state=13,class_weight='balanced').fit(X_train, y_train).predict(X_test)
f1_score(y_test,y_hat)
```

```
C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
```

Out[40]:

```
0.14056497175141244
```

Success! Balancing the model has already resulted in a dramatic performance improvement, but still not one that exceeds the Random Forest.

In [41]:

```
# LinearSVC for C
all_par = range(1,20)
scores = []
for p in all_par:
    svc = LinearSVC(random_state=13,class_weight='balanced',C=p)
    y_hat = svc.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("C", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("LinearSVC")
ax.grid(alpha=0.25)
```

```
C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
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C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
```
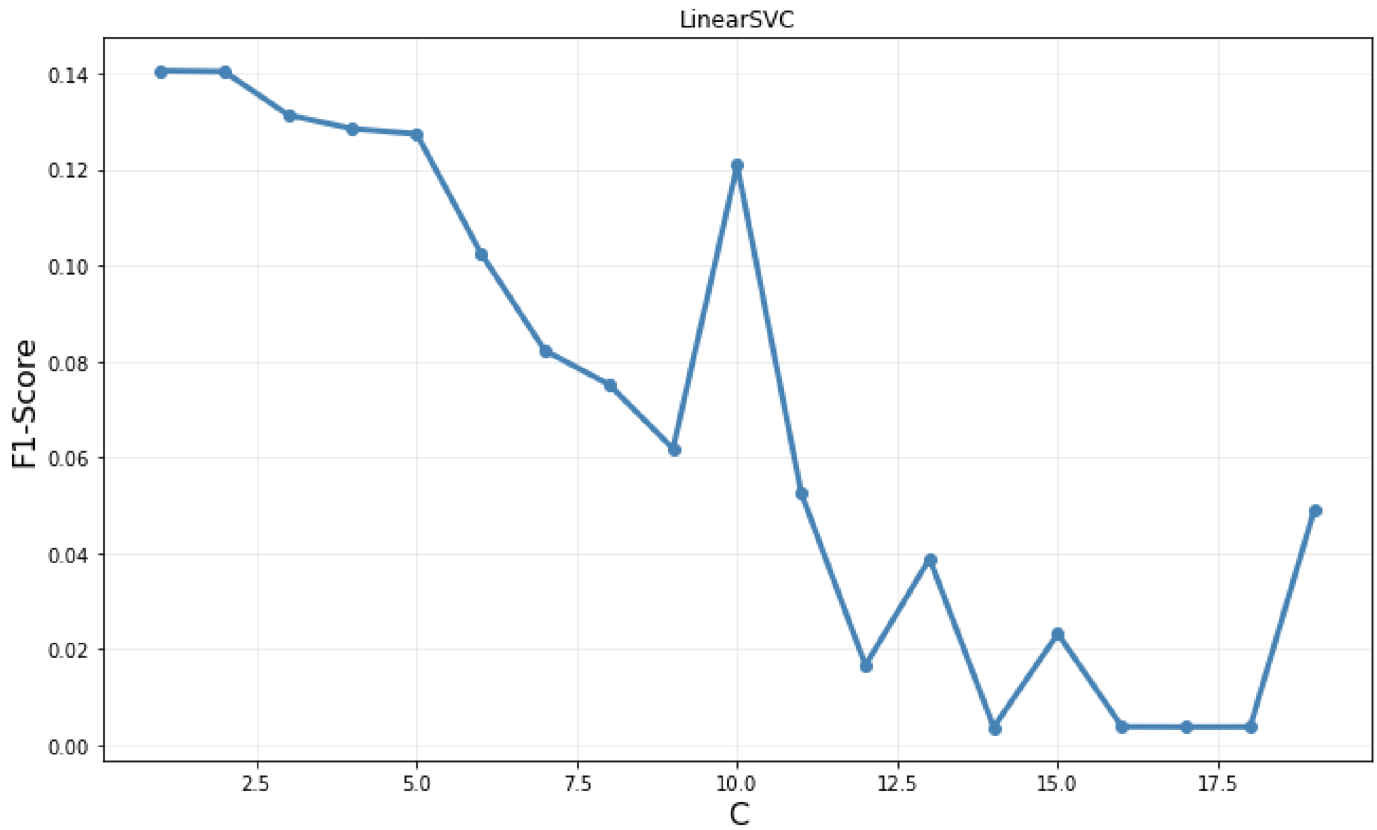

```
Maximum F1-score of  0.14056497175141244
```



In [42]:

```python
# LinearSVC for C (low values)
all_par = np.linspace(0.1,1,10)
scores = []
for p in all_par:
    svc = LinearSVC(random_state=13,class_weight='balanced',C=p)
    y_hat = svc.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("C", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("LinearSVC w/Hinge Loss")
ax.grid(alpha=0.25)
```

```
C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
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C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
```
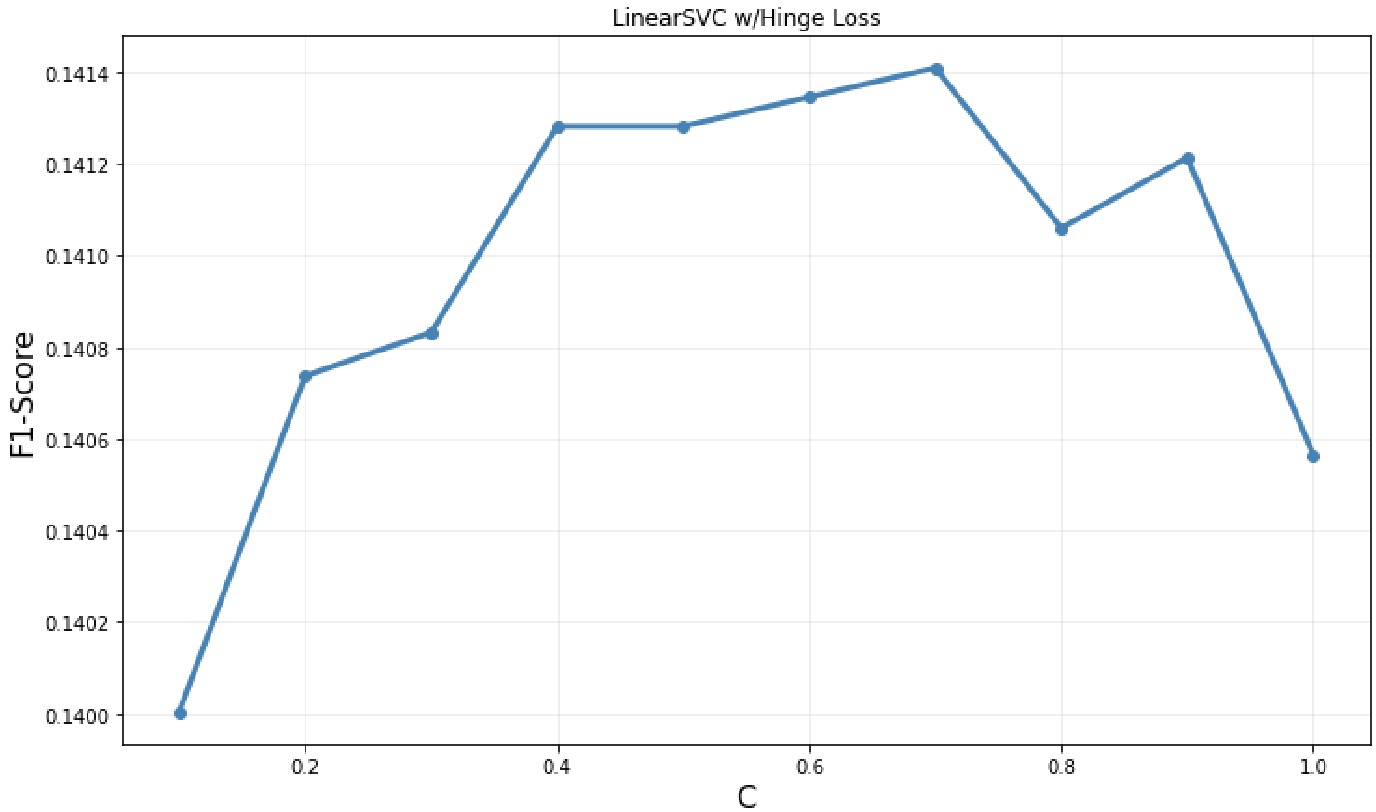

```
Maximum F1-score of  0.14140959243413648
```



In [43]:
```python
# LinearSVC for C (low values), hinge loss
all_par = np.linspace(0.1,1,10)
scores = []
for p in all_par:
    svc = LinearSVC(random_state=13,class_weight='balanced',C=p, loss='hinge')
    y_hat = svc.fit(X_train, y_train).predict(X_test)
    scores.append(f1_score(y_test,y_hat))

print('Maximum F1-score of ',max(scores))
fig, ax = plt.subplots(nrows=1,ncols=1,figsize=(12,7))
ax.plot(all_par, scores, marker="o", color="steelblue", lw=3, label="unweighted")
ax.set_xlabel("C", fontsize=16)
ax.set_ylabel("F1-Score", fontsize=16)
ax.set_title("LinearSVC w/Hinge Loss")
ax.grid(alpha=0.25)
```

```
C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
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  warnings.warn(
C:\Users\jawor\anaconda3\lib\site-packages\sklearn\svm\_base.py:1206: ConvergenceWarning: Liblin
ear failed to converge, increase the number of iterations.
  warnings.warn(
Maximum F1-score of  0.13715498938428874
```

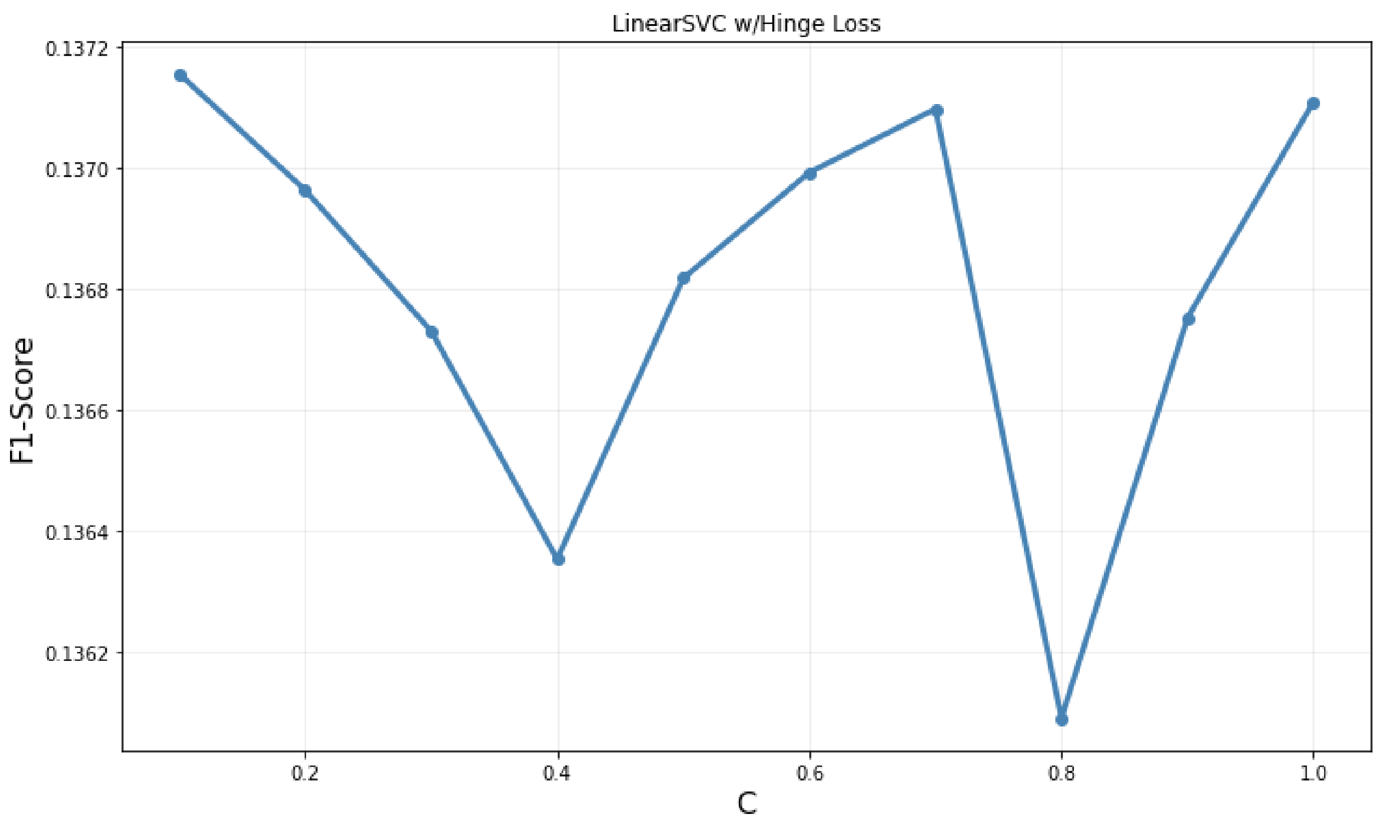

Hinge Loss hasn't improved upon the performance of the model using squared_hinge.

Discussion and Conclusion

Despite an expectation that SVM would be the best performing model and that Random Forest might not be able to handle the imbalanced data, it was the Random Forest that did the best.

Learning and Takeaways

This project made it very clear to me why imbalance must be taken into account. When first playing around with the models, I had defaulted to using accuracy as a metric (a big mistake!). The first SVM model I ran had very high accuracy, but as the F1-score proved, this was due to the model making the same prediction for all values.

What Didn’t Work

The mix of numerical and categorical features was difficult to work with. Pandas's methods tended to be more robust than SKLearn's. One example was using the one-hot encoding: pd.get_dummies encoded only the 'object' datatypes in the dataframe, whle SKLearn's encoder tried to one-hot encode the numerical features. The Classifier methods I used here all required one-hot encoding as well.

Ways to Improve

The data is potentially missing a major element: the value/expense of the claims. The performance here could be moot if it doesn't align with the economic impact of the claims (and thus the value of the predictions).