CZ1016 : Assignment

Essential Libraries

Let us begin by importing the essential Python Libraries.

> NumPy : Library for Numeric Computations in Python
> Pandas : Library for Data Acquisition and Preparation
> Matplotlib : Low-level library for Data Visualization
> Seaborn : Higher-level library for Data Visualization

In [1]:

```
# Basic Libraries
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt # we only need pyplot
sb.set() # set the default Seaborn style for graphics
```

Setup : Import the Dataset

Dataset : **"smsdata.txt"** (use `read_table` function from Pandas to import)
After importing, take a quick look at the dataset using the `head` function.

In [2]:

```
# \t because the columns are separated by a tab
# read_table to read the text file
smsData = pd.read_table('smsdata.txt', sep = "\t", header = None)
smsData.sample(n=10)
```

Out[2]:

	0	1
2323	good	Should I be stalking u?
1285	good	But if she.s drinkin i'm ok.
3415	good	No pic. Please re-send.
1627	good	Dear how you. Are you ok?
280	good	All done? All handed in? Celebrations in full ...
2784	good	Just arrived, see you in a couple days <3
4554	good	Sun ah... Thk mayb can if dun have anythin on....
3050	good	Lol they don't know about my awesome phone. I ...
1073	spam	Dear U've been invited to XCHAT. This is our f...
43	good	WHO ARE YOU SEEING?

In [3]:
```
# .columns method can rename columns
smsData.columns = ["label", "text"]
smsData.sample(n=10)
```

Out[3]:

	label	text
5293	good	I donno its in your genes or something
1855	good	They did't play one day last year know even th...
1378	spam	Double Mins & Double Txt & 1/2 price Linerenta...
1473	good	Just sent you an email – to an address with in...
3795	good	Short But Cute: "Be a good person, but dont tr...
463	spam	UpgrdCentre Orange customer, you may now claim...
5516	good	Ya, i'm referin to mei's ex wat... No ah, wait...
2136	good	Carlos took a while (again), we leave in a minute
3921	spam	FREE>Ringtone! Reply REAL or POLY eg REAL1 1. ...
1592	good	That's my honeymoon outfit. :)

In [4]:
```
# Basic information about the data
smsData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 2 columns):
label    5572 non-null object
text     5572 non-null object
dtypes: object(2)
memory usage: 87.2+ KB
```

Solution : Classification

Use the labeled (`good` / `spam`) text messages in `smsData` to build a tree-based binary classifier that is capable of distinguishing `spam` text messages from the `good` ones. You may build a single decision tree or an ensemble (forest), whichever is better in this case. Try both, and find out which one is better.

In [5]:
```python
smsData.sample(20)
```

Out[5]:

	label	text
4514	spam	Money i have won wining number 946 wot do i do...
4526	good	Cos i was out shopping wif darren jus now n i ...
3565	good	Do you always celebrate NY's with your family ?
2910	spam	URGENT! Your Mobile number has been awarded wi...
1732	good	Lol. Well quality aint bad at all so i aint co...
1149	good	I'm not driving... Raining! Then i'll get caug...
4807	good	Call me when u finish then i come n pick u.
4141	good	Leave it wif me lar... Ü wan to carry meh so h...
5468	spam	URGENT! Last weekend's draw shows that you hav...
3599	good	Aight, we'll head out in a few
3411	good	Joy's father is John. Then John is the ____ of...
3976	good	do u think that any girl will propose u today ...
24	good	Ffffffffff. Alright no way I can meet up with ...
1504	good	Ill be there on <#> ok.
1229	spam	FREE entry into our £250 weekly comp just send...
4778	good	Sorry completely forgot * will pop em round th...
2042	good	Ü dun wan to watch infernal affair?
4685	good	My life Means a lot to me, Not because I love ...
4235	good	Now only i reached home. . . I am very tired n...
5382	good	I can make it up there, squeezed <#> b...

Data exploration and feature extraction

In [6]:
```python
# likely need to convert response variable to CATEGORICAL type
# there is only ONE predictor, likely have to extract more relevant predictors for the
print("Dimensions:", smsData.shape)
print()
print("Data Types:")
print(smsData.dtypes)
```

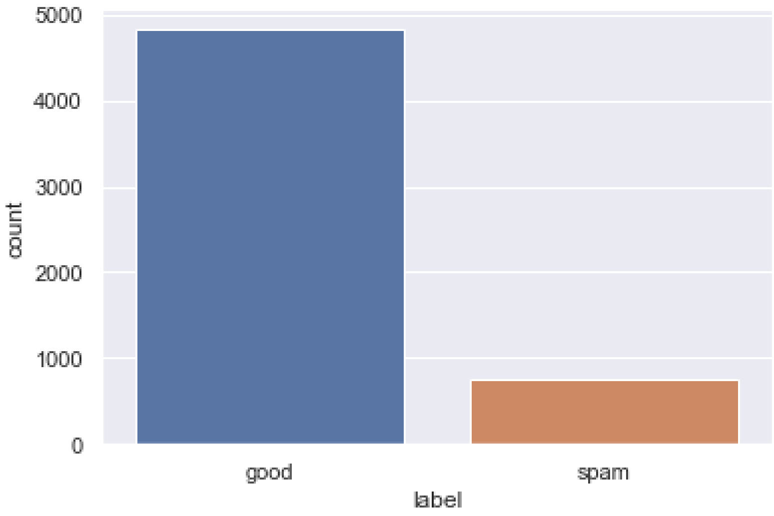
```
Dimensions: (5572, 2)

Data Types:
label     object
text      object
dtype: object
```

Visualising the response variable

- imbalanced dataset
- likely will have to balance out the data using SMOTE

In [7]:
```python
sb.countplot(smsData['label'])
```

Out[7]:
```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x1d862c155c8&gt;
```

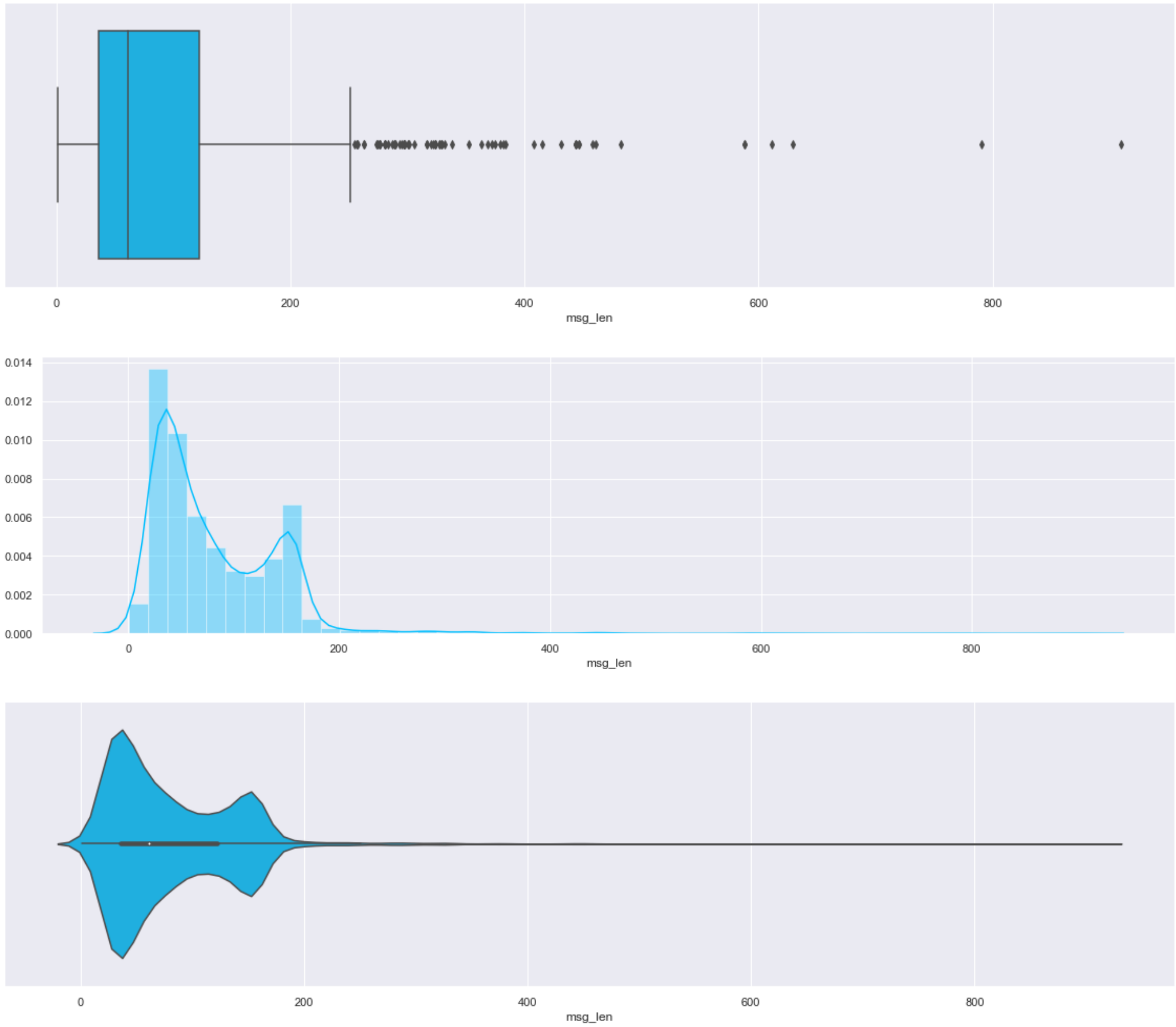


Extract length of message

In [8]:
```python
# find out if length of message length would be relevant
smsData['msg_len'] = smsData['text'].astype(str).apply(len)
```

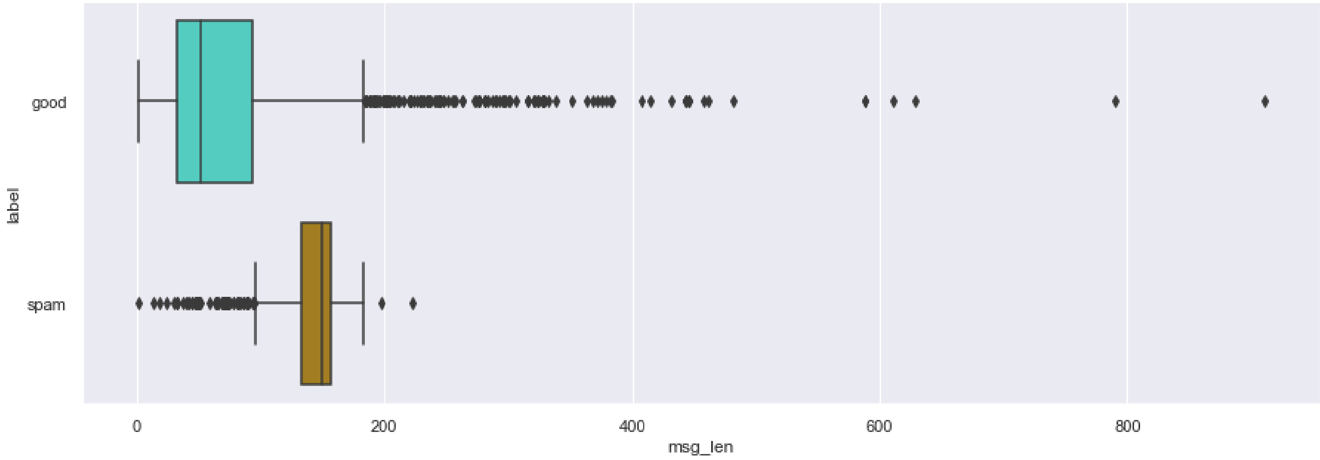
In [9]:
```python
def univariate_plots(target):
    f, axes = plt.subplots(1, 1, figsize=(20, 5))
    sb.boxplot(smsData[target], color = "deepskyblue")
    f, axes = plt.subplots(1, 1, figsize=(20, 5))
    sb.distplot(smsData[target], color = "deepskyblue")
    f, axes = plt.subplots(1, 1, figsize=(20, 5))
    sb.violinplot(smsData[target], color = "deepskyblue")
```

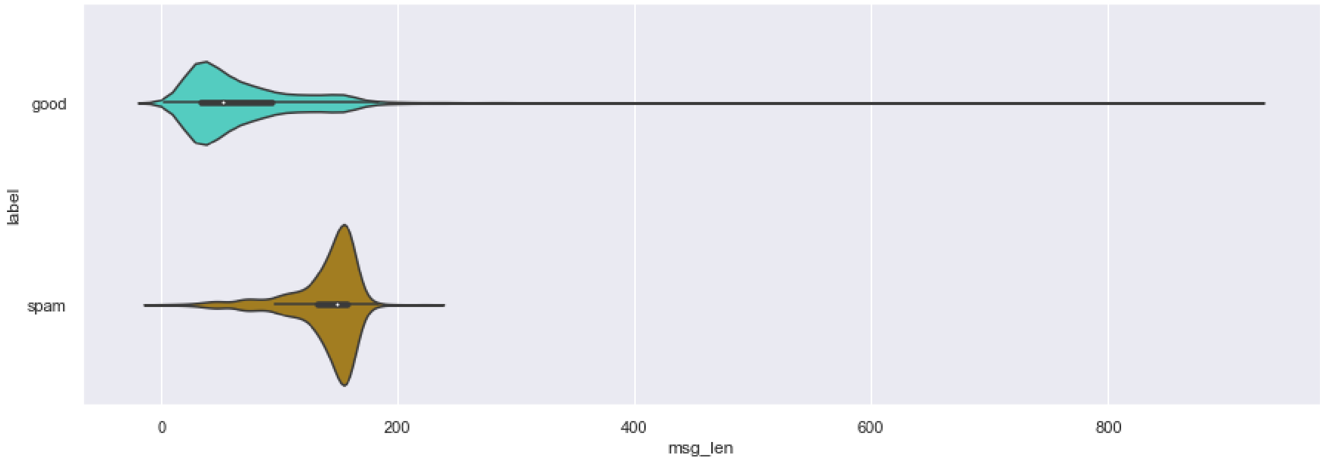
In [10]:
```
# more than 50% of the rows are less than 100 in length
# there are a bunch of outliers
# there seems to be 2 concentrations on length; one at 50 and the other at 150
univariate_plots('msg_len')
```



In [11]:
```
def multivariate_plots(target):
    f, axes = plt.subplots(1, 1, figsize=(15, 5))
    sb.boxplot(x=target,y='label',data=smsData,palette=['turquoise','darkgoldenrod'])
    f, axes = plt.subplots(1, 1, figsize=(15, 5))
    sb.violinplot(x=target,y='label',data=smsData,palette=['turquoise','darkgoldenrod']
```

In [12]:
```
# Observation: most 'spam' length is concentrated at around 150 while 'good' is around :
# above 200, rows are very likely to be 'good'
multivariate_plots('msg_len')
```





In [13]:
```
pd.crosstab(smsData['msg_len'].apply(lambda x: 100<x<200), smsData['label'])
```

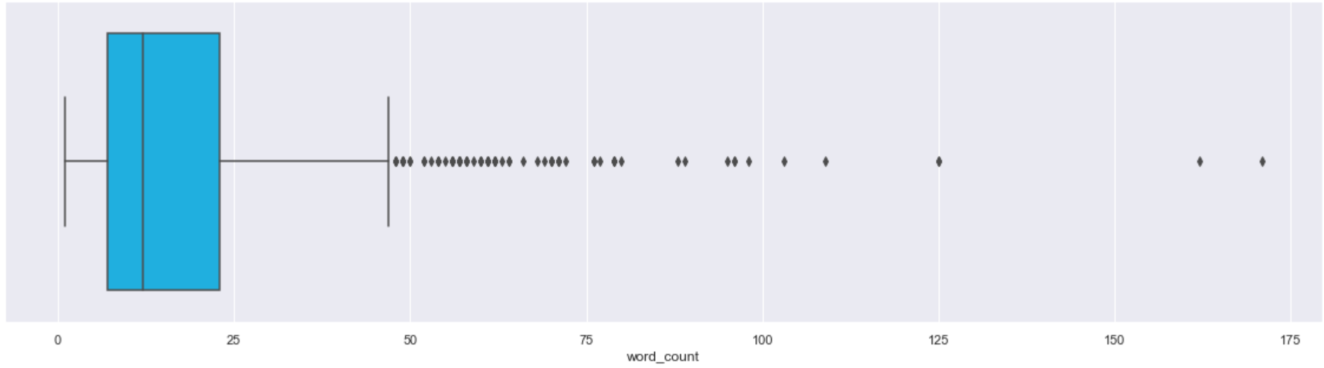
Out[13]:

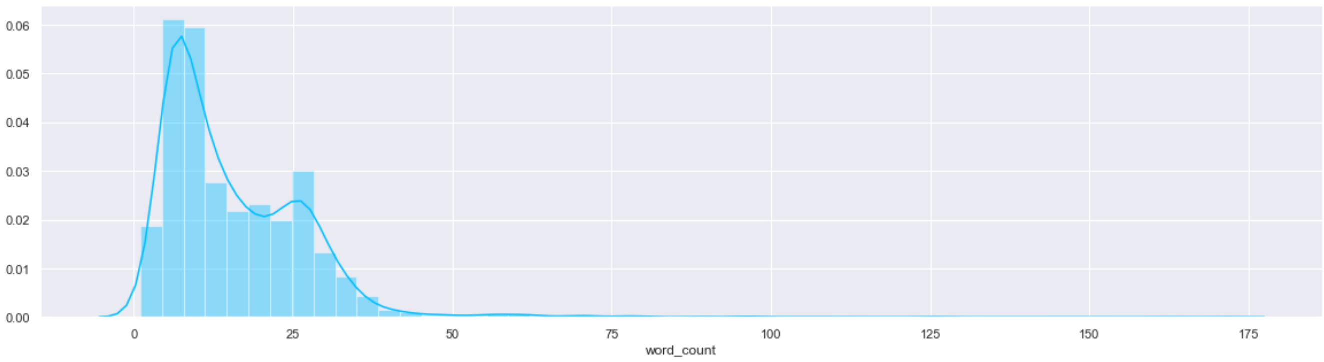
label	good	spam
msg_len		
False	3846	78
True	979	669

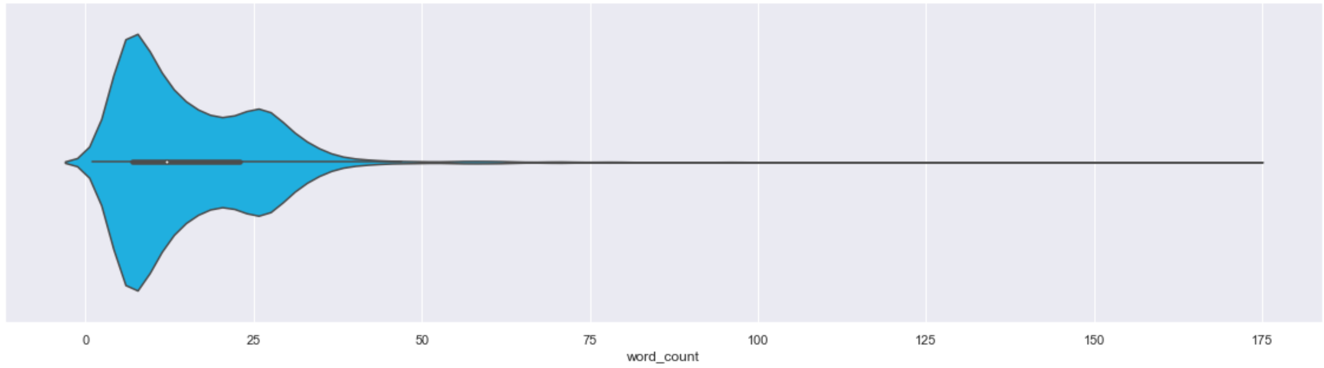
Extract word counts

In [14]:
```
smsData['word_count'] = smsData['text'].apply(lambda x: len(str(x).split()))
```

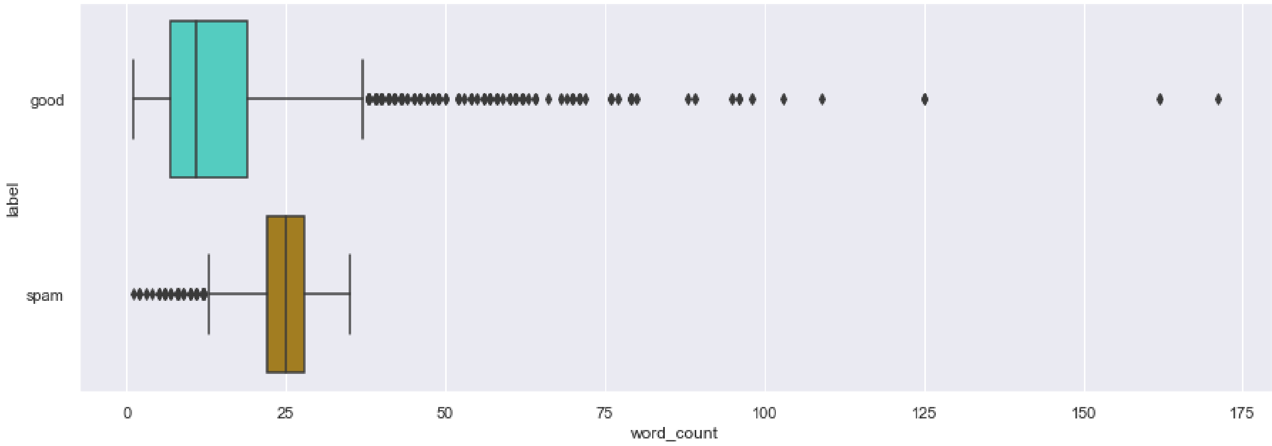
In [15]:
```python
# this feature is correlated with message length, likely take one or the other
univariate_plots('word_count')
```





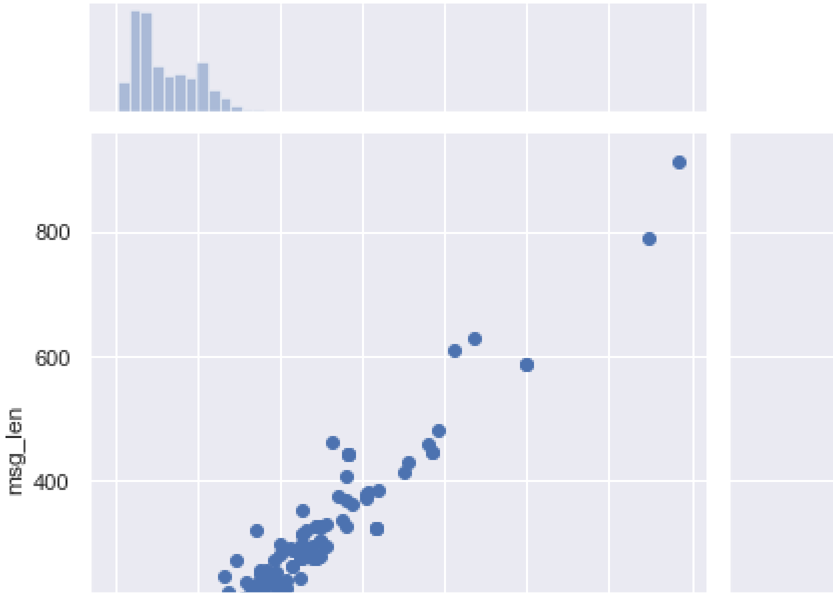


In [16]:
```python
# very similar result with message length
multivariate_plots('word_count')
```



In [17]:
```
## comapring word count to message length
sb.jointplot(smsData['word_count'],smsData['msg_len'])
```

Out[17]: <seaborn.axisgrid.JointGrid at 0x1d8655b2208>



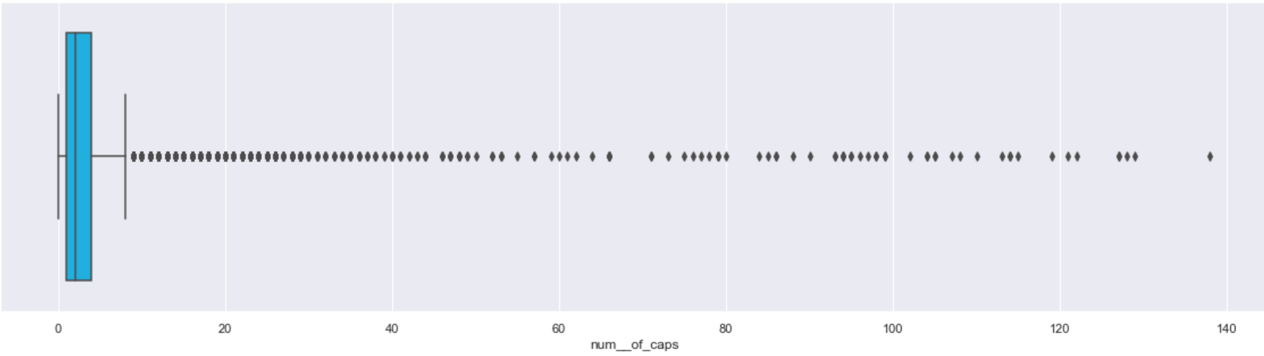
In [18]:
```
# drop word_wount because it is highly correlated to msg_le
smsData=smsData.drop(['word_count'],axis=1)
```

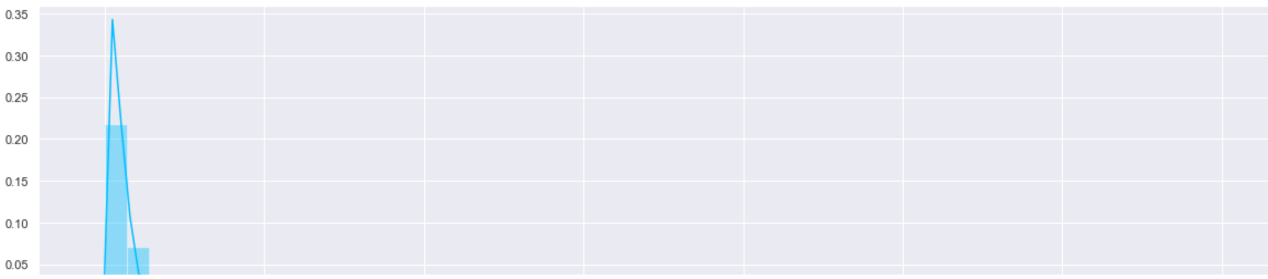
Extract number of capital letters

- hypothesis: 'spam' would tend to have more captial letters

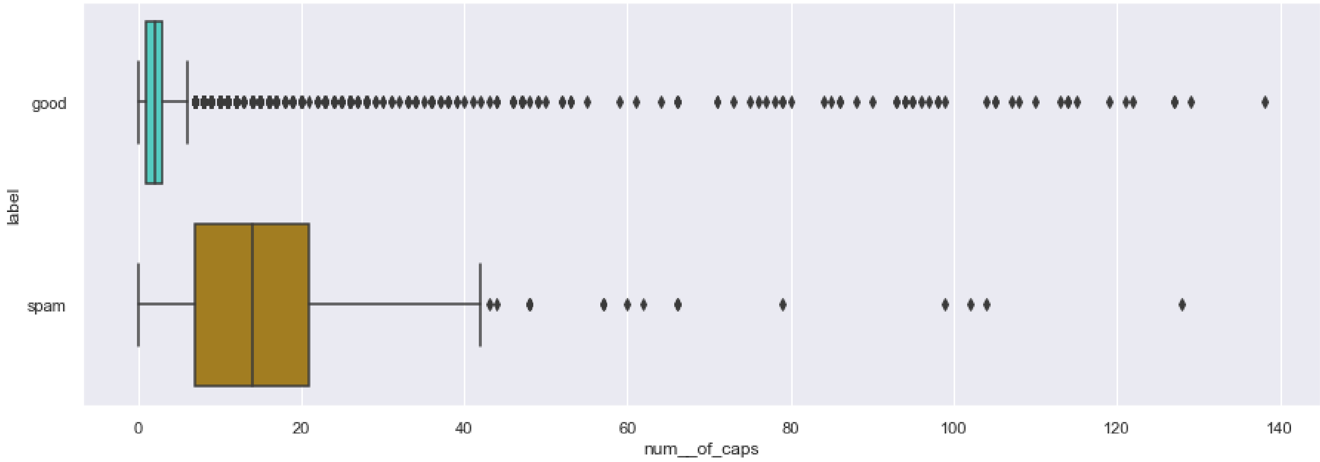
In [19]:
```
smsData['num__of_caps']=smsData['text'].apply(lambda x: len([x for x in str(x) if x.isu
```

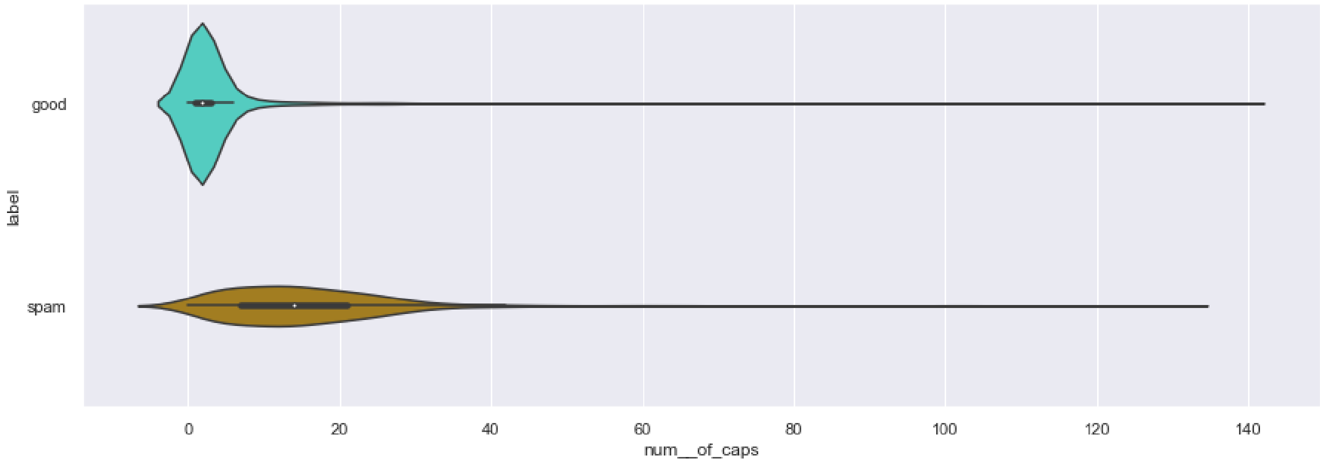
In [20]:
```
# large majority of rows have less than 10 caps
univariate_plots('num__of_caps')
```





In [21]:
```
# 'spam' does tend to have more caps, but this doesn't seem to be a very good predictor
#because there are also lots of 'good' with many caps
multivariate_plots('num__of_caps')
```





In [22]:
```
# above 5 caps over 50% are 'spam'
pd.crosstab(smsData['num__of_caps'].apply(lambda x: 5<x), smsData['label'])
```

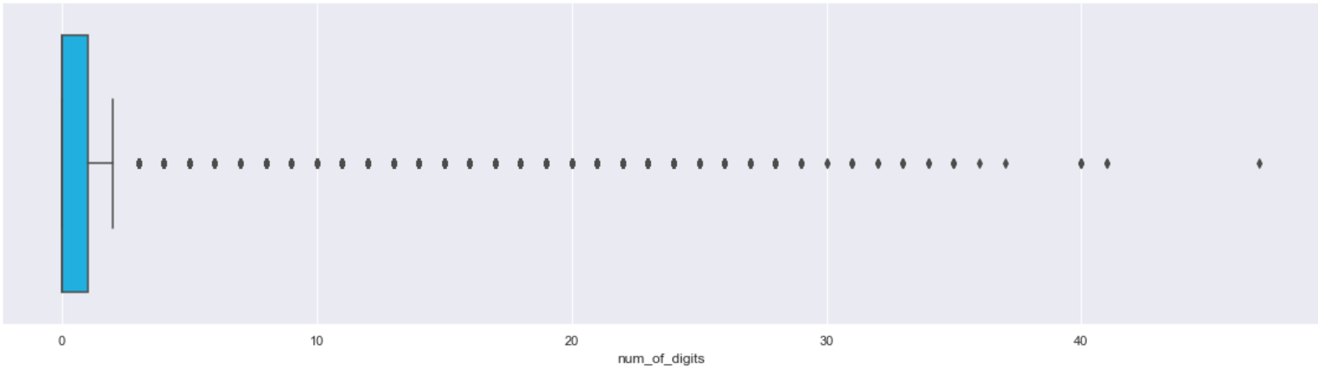
Out[22]:

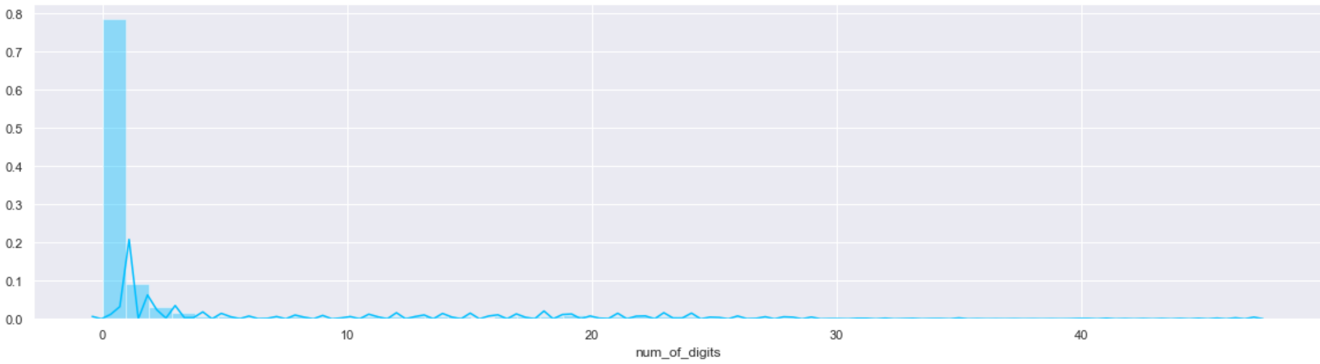
label	good	spam
num__of_caps		
False	4305	135
True	520	612

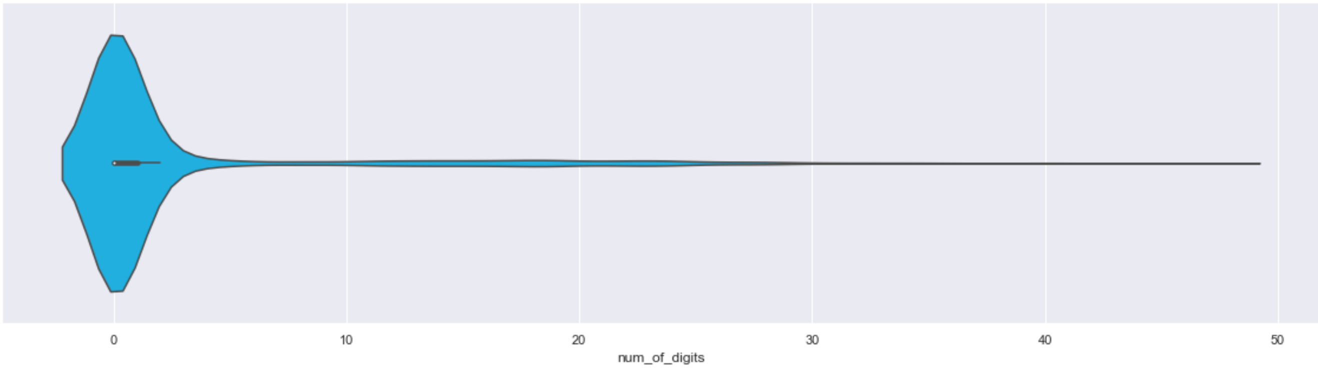
Extract number of digits

In [23]:
```
smsData['num_of_digits']=smsData['text'].apply(lambda x: len([x for x in str(x) if x.is
```

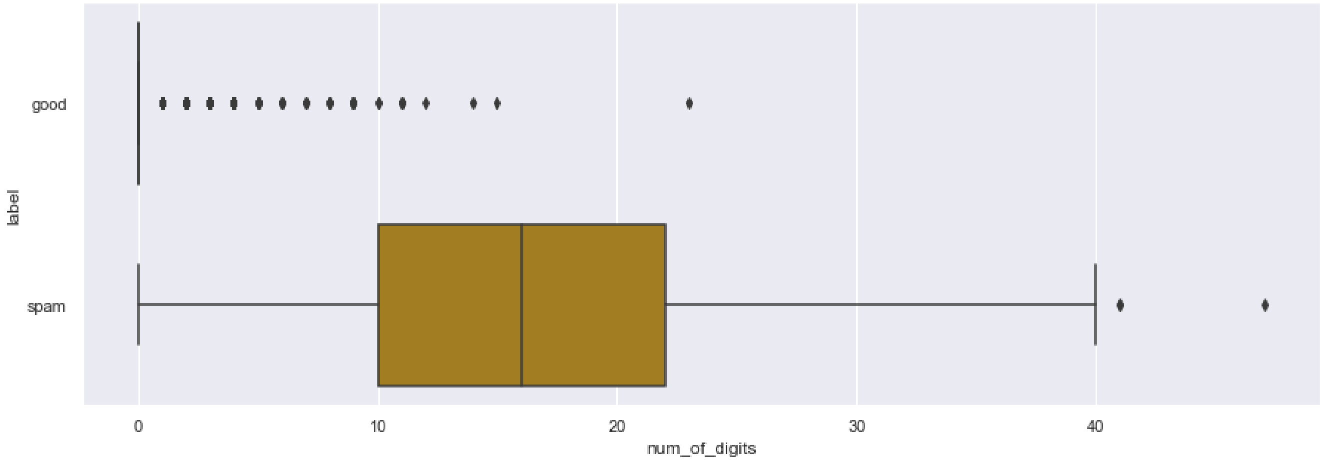
In [24]:
```
# most rows have little to no digits
univariate_plots('num_of_digits')
```

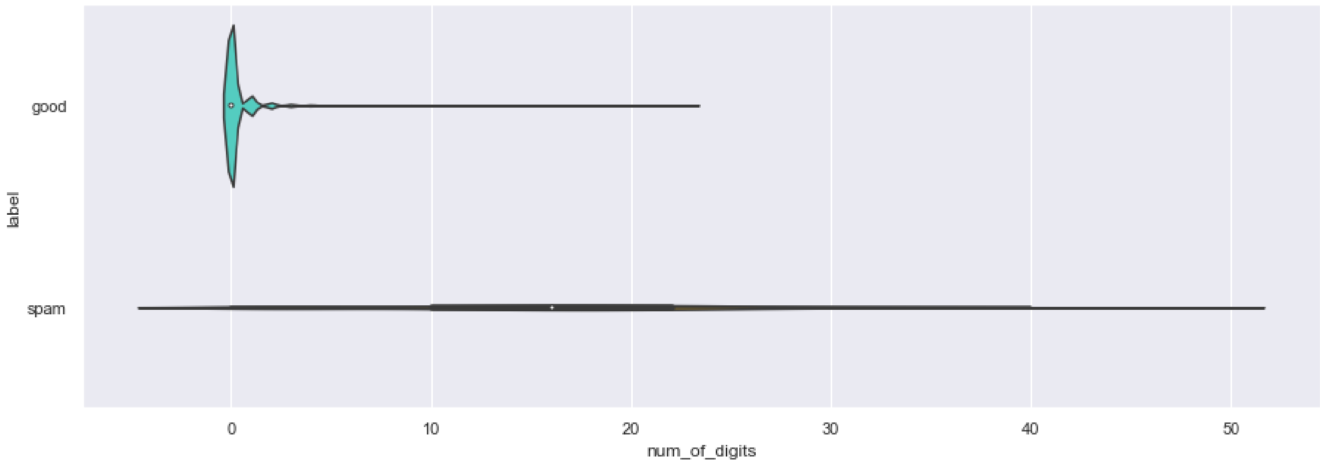






In [25]:
```
# 'spam' emails tend to have a lot more digits than 'good'
multivariate_plots('num_of_digits')
```





In [26]:
```python
# there are also 'good' with many digits
#'good' with more than 5 digits
smsData.loc[(smsData['num_of_digits']>10)&(smsData['label']=='good')]
```

Out[26]:

	label	text	msg_len	num__of_caps	num_of_digits
692	good	Sorry to trouble u again. Can buy 4d for my da...	109	4	15
989	good	Yun ah.the ubi one say if ü wan call by tomorr...	160	2	23
2408	good	Solve d Case : A Man Was Found Murdered On &l...	444	44	11
2681	good	Solve d Case : A Man Was Found Murdered On &l...	444	44	11
2933	good	Only 2% students solved this CAT question in '...	183	5	14
3280	good	Solve d Case : A Man Was Found Murdered On &l...	444	44	11
3291	good	My tuition is at 330. Hm we go for the 1120 to...	69	3	11
3462	good	K.. I yan jiu liao... Sat we can go 4 bugis vi...	155	4	12
4762	good	It's é only $140ard...Érestallard$180 at ...	89	3	11

In [27]:
```python
# above 10 digits, the email is very likely to be 'spam'
pd.crosstab(smsData['num_of_digits'].apply(lambda x: x>10), smsData['label'])
```

Out[27]:

label	good	spam
num_of_digits		
False	4816	189
True	9	558

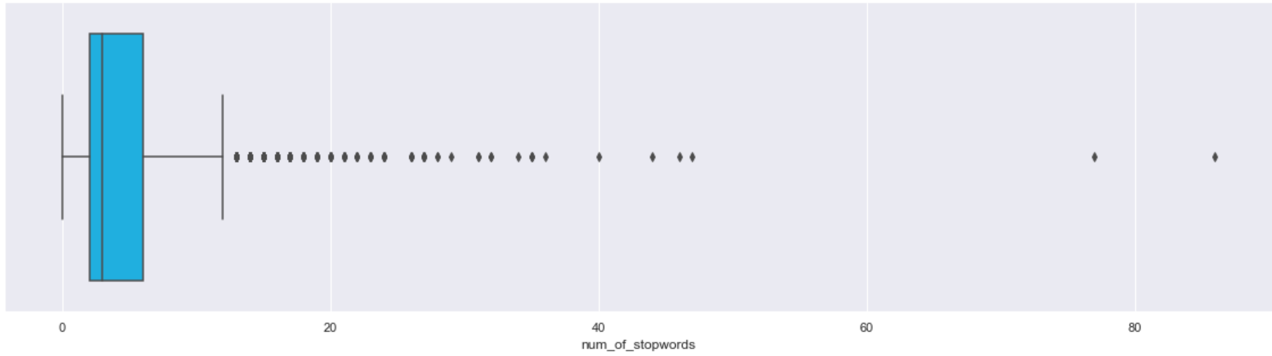
extract number of stopwords

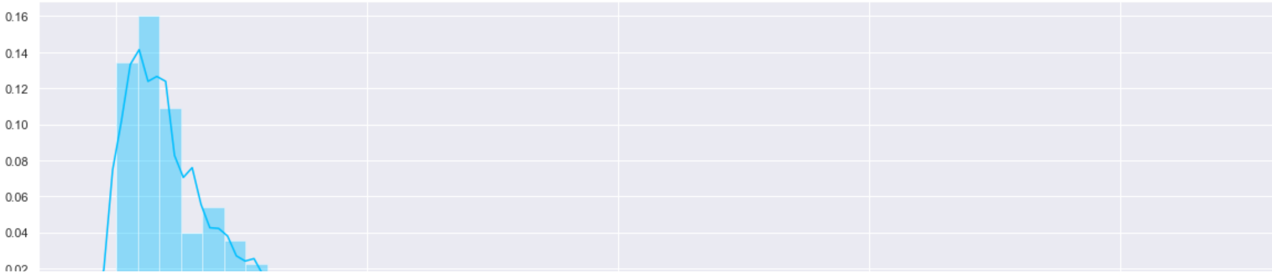
    - although all, data points more than 20 stopwords are 'good', this seems to be
    a poor indicator

In [28]:
```python
from nltk.corpus import stopwords
stop=stopwords.words('english')
```

In [29]:
```python
smsData['num_of_stopwords']=smsData['text'].apply(lambda x: len([x for x in x.split() i
```

In [30]:
```python
univariate_plots('num_of_stopwords')
```

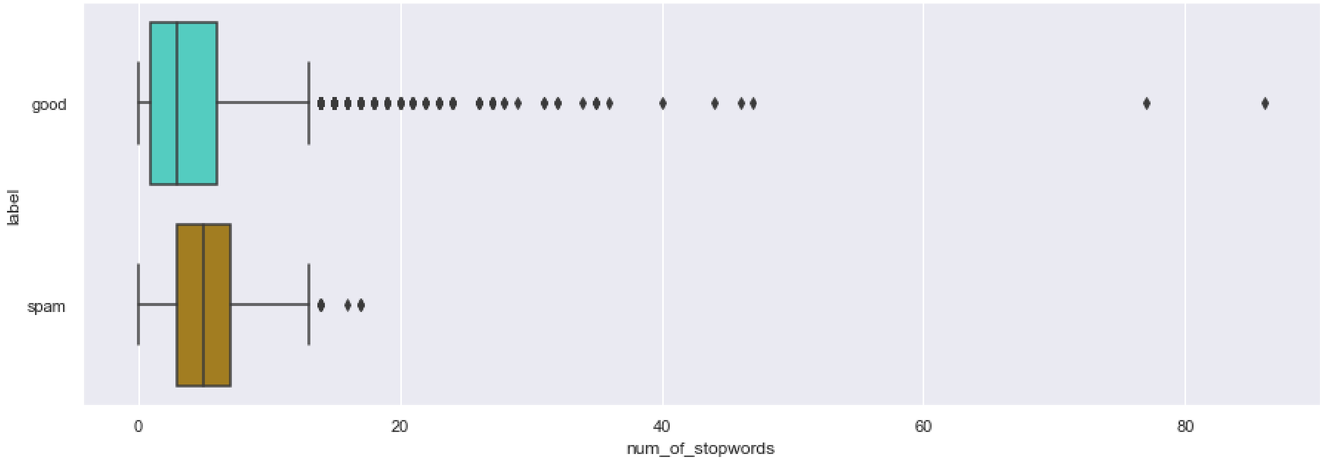


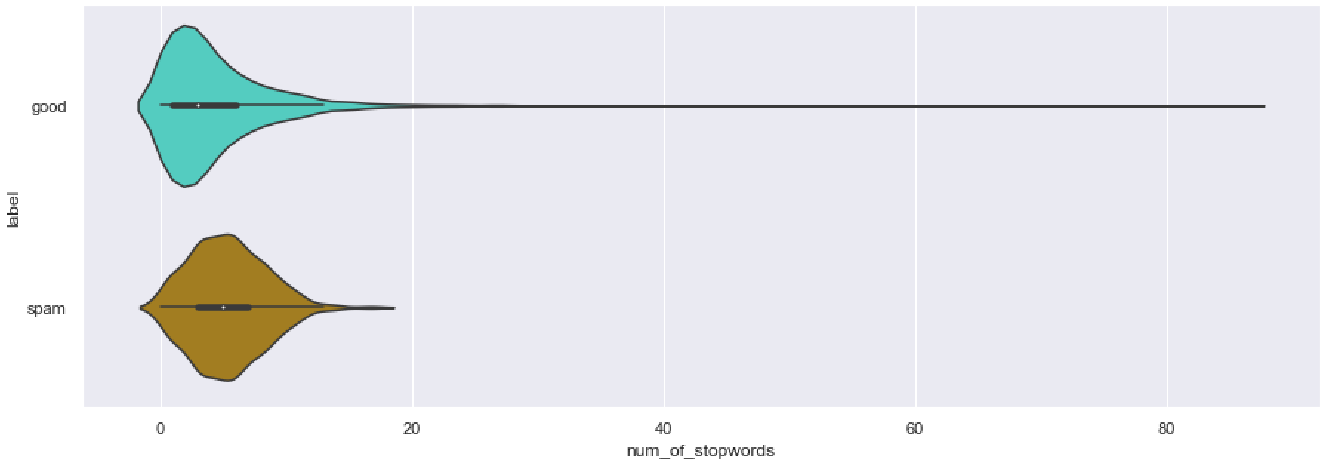


In [31]:
```python
# 50% of rows have 2 to 6 stopwords
smsData['num_of_stopwords'].describe()
```

Out[31]:
```
count    5572.000000
mean        4.596554
std         4.591812
min         0.000000
25%         2.000000
50%         3.000000
75%         6.000000
max        86.000000
Name: num_of_stopwords, dtype: float64
```

In [32]:
```
# above 20 stopwords the email is like 'good'
multivariate_plots('num_of_stopwords')
```





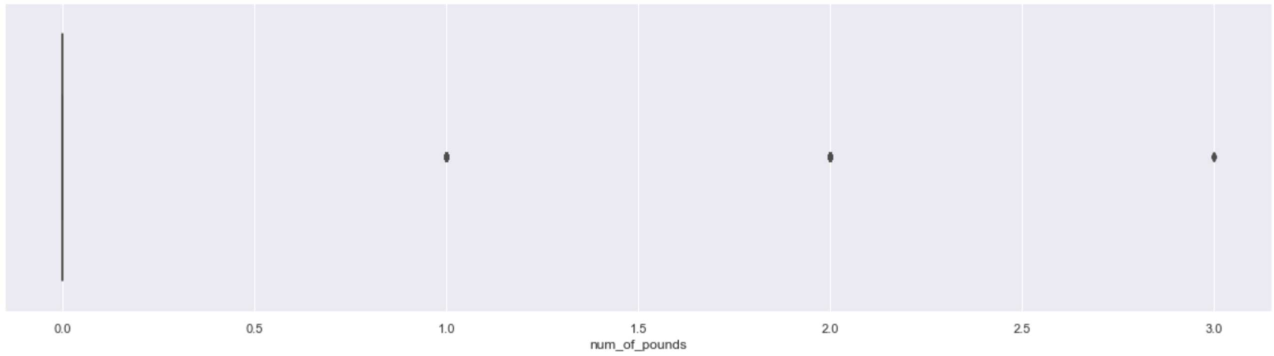
In [33]:
```
# this feature does not a very good predictor looking at the multivariate plot
smsData=smsData.drop(['num_of_stopwords'],axis=1)
```

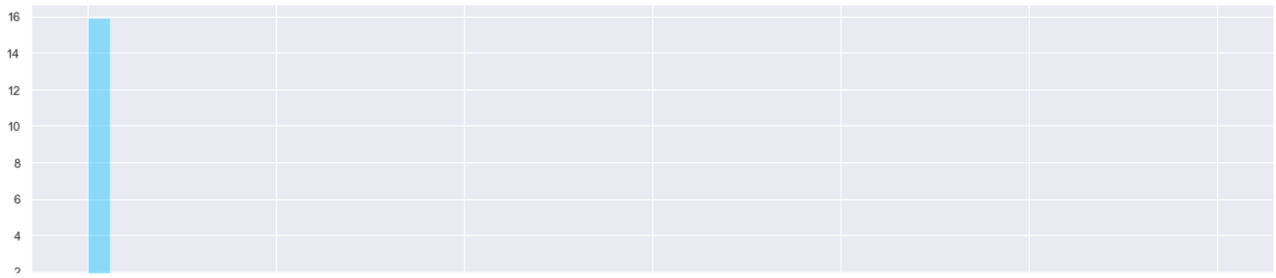
extract number of 'pounds' sign

- hyppthesis is that pounds sign can indicate 'spam' that is asking for money

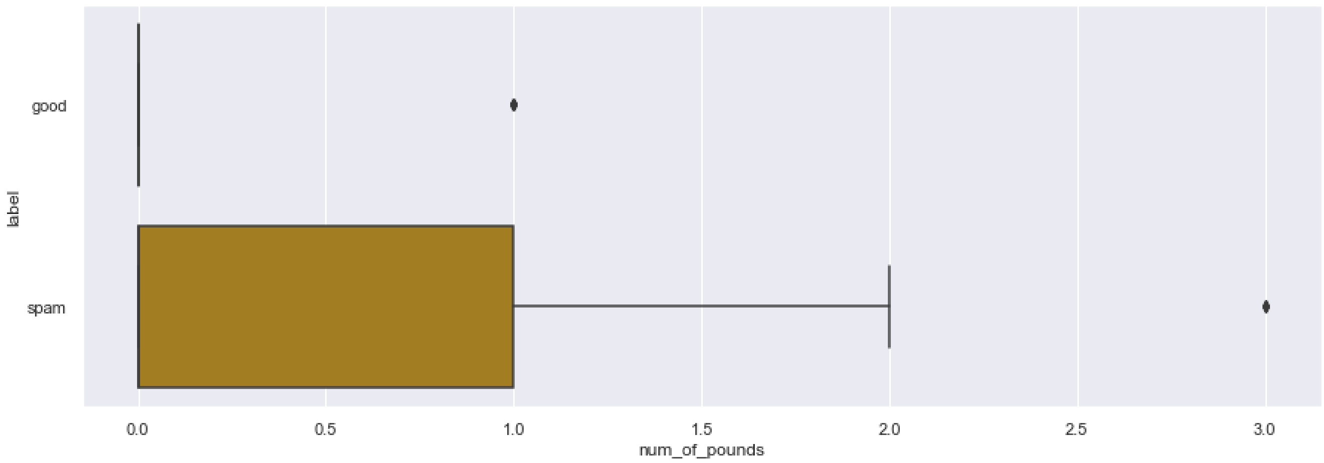
In [34]:
```
smsData['num_of_pounds']=smsData['text'].apply(lambda x: len([x for x in str(x) if x=='
```

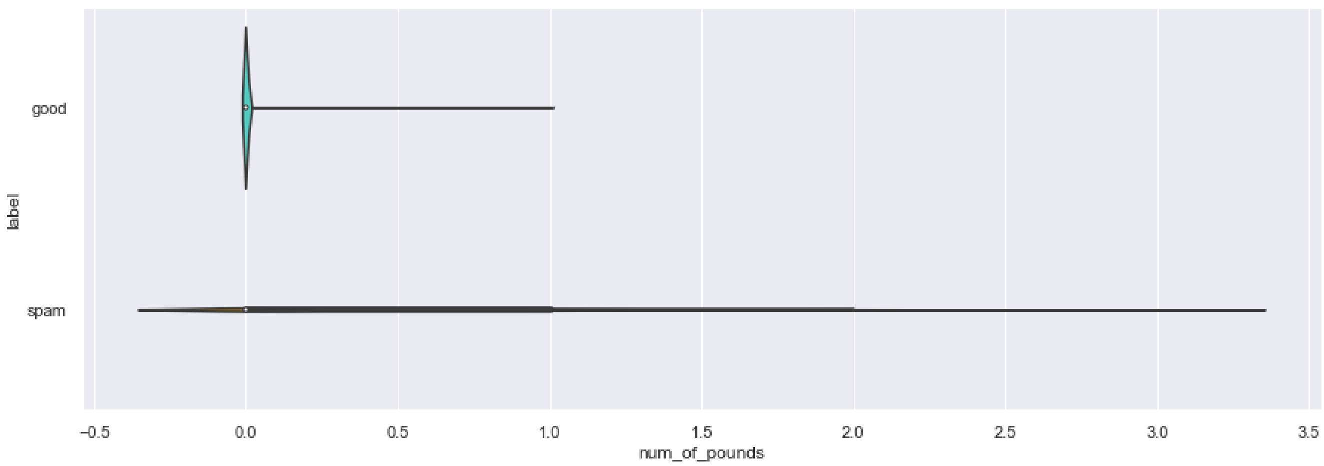
In [35]:
```python
# most rows have no pounds sign
univariate_plots('num_of_pounds')
```





In [36]:
```python
# if there is a pounds sign, it is very likely to be 'spam'
multivariate_plots('num_of_pounds')
```





In [37]:
```python
# 'good' with pounds sign
smsData.loc[(smsData['num_of_pounds']>0)&(smsData['label']=='good')]
```

Out[37]:

	label	text	msg_len	num__of_caps	num_of_digits	num_of_pounds
1677	good	Yeah, that's fine! It's £6 to get in, is that ok?	49	2	1	1
1724	good	Hi Jon, Pete here, Ive bin 2 Spain recently & ...	157	8	8	1
1998	good	YEH I AM DEF UP4 SOMETHING SAT,JUST GOT PAYED2...	149	113	6	1
3044	good	Your bill at 3 is £33.65 so thats not bad!	42	1	5	1
3736	good	It‘s £6 to get in, is that ok?	30	1	1	1

In [38]:
```python
# if there is a pounds sign, it is very likely to be 'spam'
pd.crosstab(smsData['num_of_pounds'].apply(lambda x: x>0), smsData['label'])
```

Out[38]:

label	good	spam
num_of_pounds		
False	4820	494
True	5	253

extract presence of a link

- hypothesis is that a link would suggest 'spam' that want the victim to click to another website

In [39]:
```python
smsData['link_present']=smsData['text'].apply(lambda x: 'www.' in str(x).lower() or 'ht
```

In [40]:
```python
# indeed if a link is present, it is likely spam. it accounts for a very small percenta
pd.crosstab(smsData['link_present'], smsData['label'])
```

Out[40]:

label	good	spam
link_present		
False	4823	640
True	2	107

In [41]:
```python
# 'good' with link present
smsData.loc[(smsData['link_present'])&(smsData['label']=='good'),['text','link_present'
```

Out[41]:

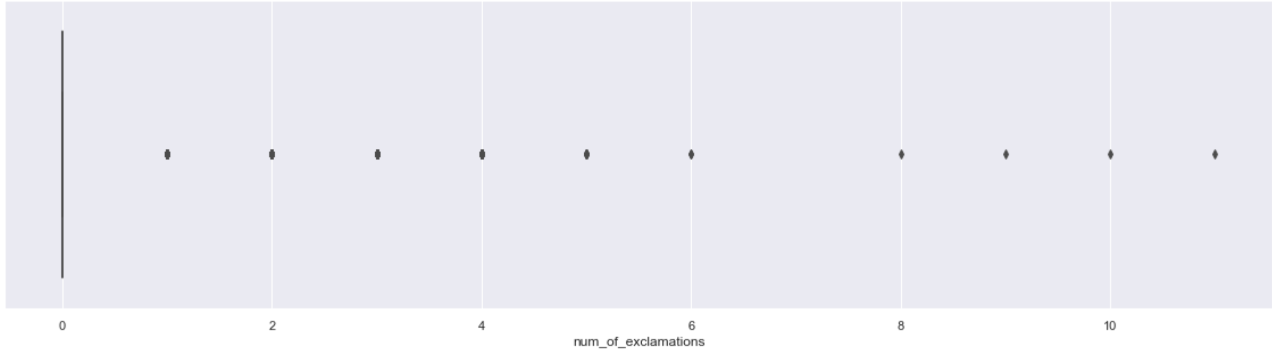
	text	link_present
2379	Hi, Mobile no. <#> has added you in th...	True
4773	Hi, Mobile no. <#> has added you in th...	True

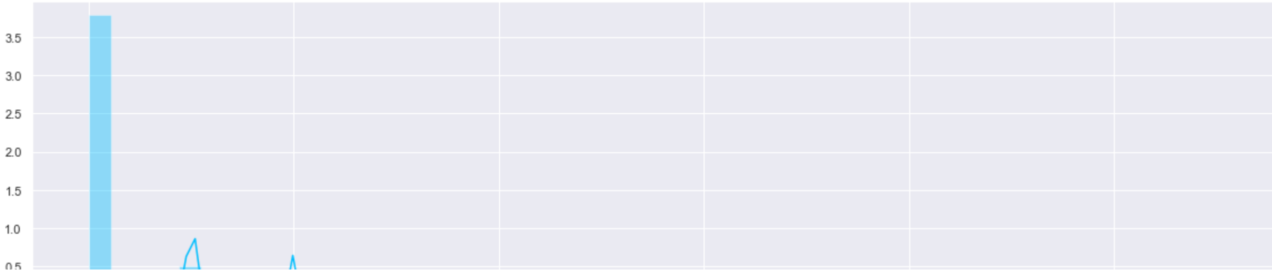
extract number of exclamations

- hypothesis was that presence of more exclamation mark would indicate 'spam'

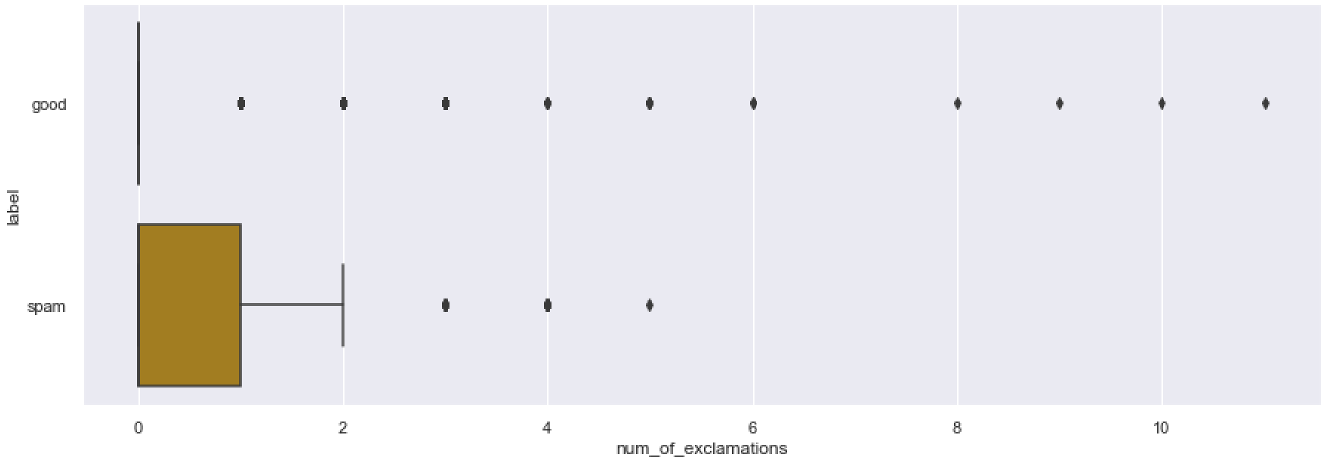
In [42]:
```
smsData['num_of_exclamations']=smsData['text'].apply(lambda x: len([x for x in str(x) i
```

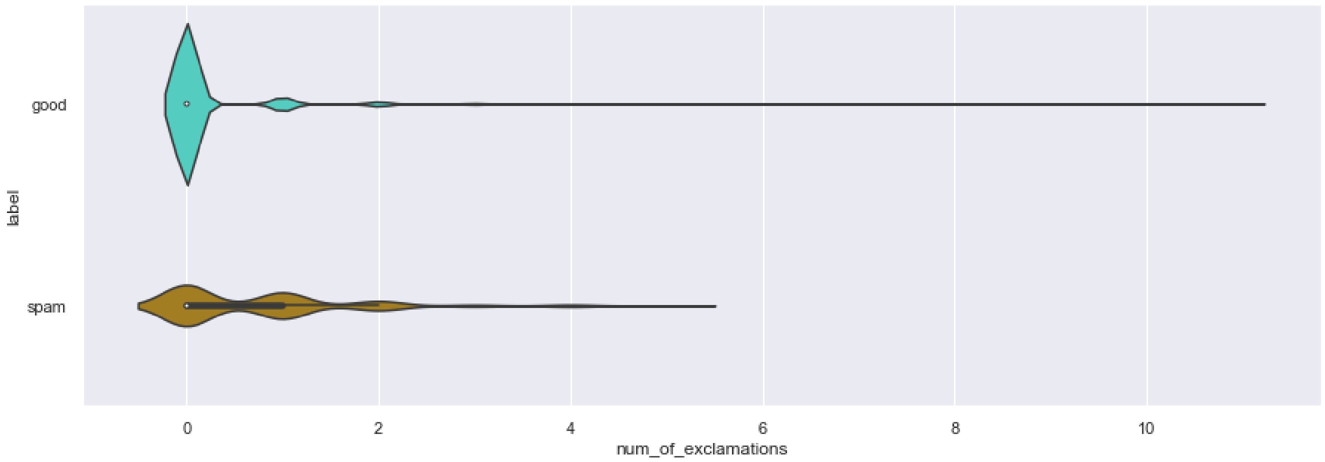
In [43]:
```
# large majority of emails have little to none
univariate_plots('num_of_exclamations')
```





In [44]:
```
# around 50 % of 'spam' emails do have '!' have there are also quite a number of 'good'
multivariate_plots('num_of_exclamations')
```





In [45]:
```
# 'good' with exclamations
smsData.loc[(smsData['num_of_exclamations']>0)&(smsData['label']=='good')]
```

Out[45]:

	label	text	msg_len	num__of_caps	num_of_digits	num_of_pounds	link_present	num_of_excl
14	good	I HAVE A DATE ON SUNDAY WITH WILL!!	35	26	0	0	False	
29	good	Ahhh. Work. I vaguely remember that! What does...	64	5	0	0	False	
31	good	Yeah he got in at 2 and was v apologetic. n ha...	188	5	2	0	False	
39	good	Hello! How's you and how did saturday go? I wa...	155	4	0	0	False	
44	good	Great! I hope you like your man well endowed. ...	72	3	0	0	False	
...	...	...	...	...	...	...	...	
5465	good	Shall I bring us a bottle of wine to keep us a...	87	4	0	0	False	
5476	good	Yes princess! I want to please you every night...	74	3	0	0	False	
5480	good	Have you seen who's back at Holby?!	35	2	0	0	False	
5494	good	Cool, we shall go and see, have to go to tip a...	155	4	0	0	False	
5506	good	God's love has no limit. God's grace has no me...	149	6	1	0	False	

562 rows × 8 columns

In [46]:
```python
# around 50% of 'spam' have '!',
pd.crosstab(smsData['num_of_exclamations'].apply(lambda x: x>0), smsData['label'])
```

Out[46]:

label	good	spam
num_of_exclamations		
False	4263	381
True	562	366

extract presence of consecutive dots '..'

- looking at the raw data, 'good' emails tend to have this, let's take a look

In [47]:
```python
smsData['consecutiveDots']=smsData['text'].apply(lambda x: '..' in str(x))
```

In [48]:
```python
# emails are very likely to be 'good' when '..' is present
pd.crosstab(smsData['consecutiveDots'], smsData['label'])
```

Out[48]:

label	good	spam
consecutiveDots		
False	3702	730
True	1123	17

In [49]:
```python
# 'spam' with consecutive dots
smsData.loc[(smsData['consecutiveDots'])&(smsData['label']=='spam')]
```

Out[49]:

	label	text	msg_len	num__of_caps	num_of_digits	num_of_pounds	link_pre
1366	spam	HOT LIVE FANTASIES call now 08707509020 Just 2...	101	29	23	0	F
1374	spam	Bears Pic Nick, and Tom, Pete and ... Dick. In...	151	7	25	0	F
1734	spam	Hi, this is Mandy Sullivan calling from HOTMIX...	223	14	23	1	F
2003	spam	TheMob>Yo yo yo-Here comes a new selection of ...	143	9	0	0	F
2247	spam	Hi ya babe x u 4goten bout me?' scammers getti...	181	4	1	0	F
2313	spam	tddnewsletter@emc1.co.uk (More games from TheD...	114	10	1	0	F

extract happy faces

- hypothesis is that happy faces indicate non-sinister intent which are 'good' emails

In [50]:
```
# 100% of emails with happy faces are 'good'
smsData['happy_face']=smsData['text'].apply(lambda x: ':)' in str(x) or ':-)' in str(x)
pd.crosstab(smsData['happy_face'], smsData['label'])
```

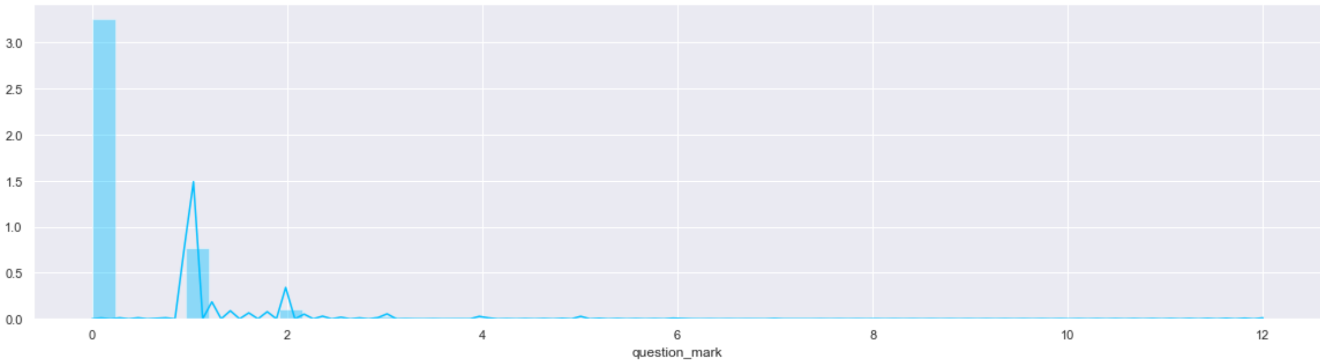
Out[50]:

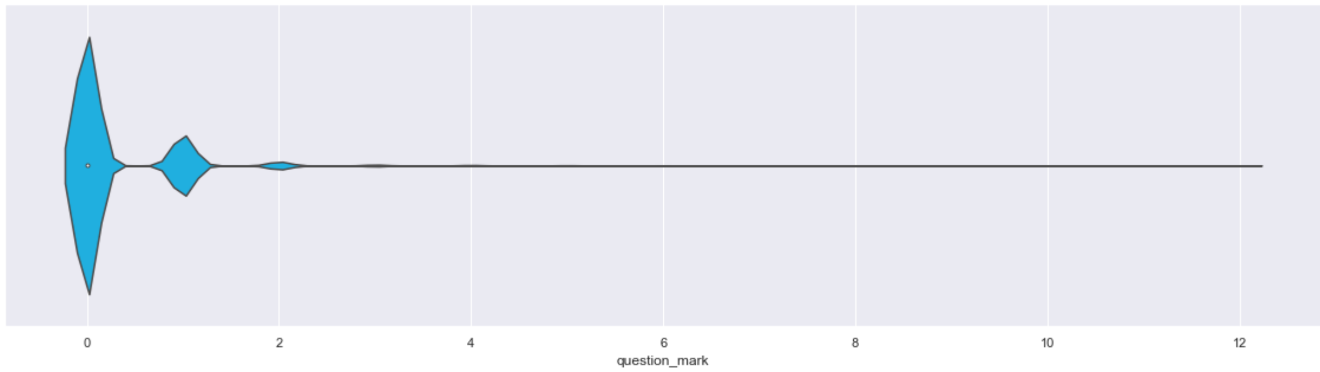
label	good	spam
happy_face		
False	4529	747
True	296	0

Number of question marks

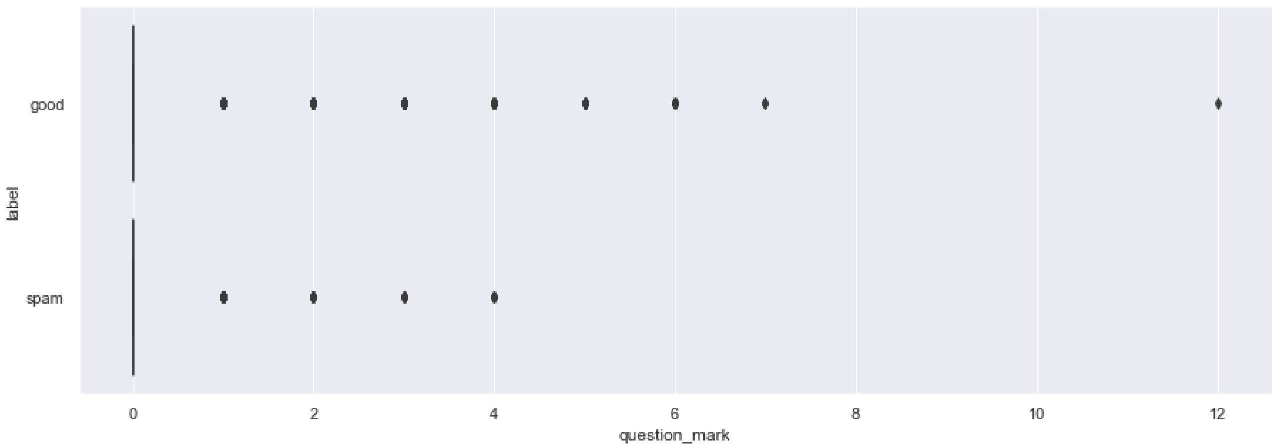
In [51]:
```
smsData['question_mark']=smsData['text'].apply(lambda x: len([i for i in str(x) if i=='
```

In [52]:
```python
# majority of rows have none, though there are plenty of outliers
univariate_plots('question_mark')
```





In [53]:
```python
## does seem to predict 'good' when quantity is high
multivariate_plots('question_mark')
```



In [54]:
```
## dropped this feature because it is not a significant enough predictor
smsData=smsData.drop(['question_mark'],axis=1)
```

In [55]:
```
new_features=[col for col in smsData.columns if( col not in ['label','text'])]
print("Additional features extracted: ")
for i,col in enumerate(new_features):
    print(i+1,col)
```

```
Additional features extracted:
1 msg_len
2 num__of_caps
3 num_of_digits
4 num_of_pounds
5 link_present
6 num_of_exclamations
7 consecutiveDots
8 happy_face
```

Pre-processing

convert text to lower case

- x.split() splits by empty space, so we have a LIST OF WORDS
- " ".join converts this list back into a SENTENCE

In [56]:
```
smsData['text']=smsData['text'].apply(lambda x: " ".join(x.lower() for x in x.split()))
```

extract only alphabets

- special characters and all punctuations would be removed
- [^a-zA-Z] means to exclude a-z and A-Z

In [57]:
```
import re
smsData['text']=smsData['text'].apply(lambda x: re.sub('[^a-zA-Z]',' ',x))
```

remove punctuations(disabled)

- this step is already account in the previous cell
- using .replace method

```
smsData['text']=smsData['text'].str.replace('[^\w\s]','')
```

remove stopwords

-ie unimportant words

In [58]:
```
from nltk.corpus import stopwords
stop = stopwords.words('english')
smsData['text']=smsData['text'].apply(lambda x: " ".join(x for x in x.split() if x not
```

take only most frequent words

- rare words are just add to noise
- Dilemma: at what point do we call a word rare and remove it?
- Note: we should keep mopst FREQUENT words because some of them like ' call' or ' free' help predict 'spam'

In [59]:
```
freq=pd.Series(' '.join(smsData['text']).split()).value_counts()
most_freq=freq[:300]
```

In [60]:
```
smsData['text']=smsData['text'].apply(lambda x: " ".join(x for x in x.split() if x in m
```

remove leftover single letters

- it seems, there are single letters scattered around
- remove them because they likely do not add any meaning

In [61]:
```
smsData['text']=smsData['text'].apply(lambda x: " ".join(x for x in x.split() if len(x)
```

lemmatization

- convert words to roots

In [62]:
```
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()

smsData['text']=smsData['text'].apply(lambda x: " ".join([lemmatizer.lemmatize(x) for w
```

creating the bag of words model

- a sparse matrix where each column represents a word

In [63]:
```
from sklearn.feature_extraction.text import CountVectorizer
cv=CountVectorizer()
X=cv.fit_transform(smsData['text']).toarray()
X=pd.DataFrame(X)
```

In [64]:
```python
X.head()
```

Out[64]:

	0	1	2	3	4	5	6	7	8	9	...	281	282	283	284	285	286	287	288	289	290
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	5	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 291 columns

In [65]:
```python
# adding the engineered features
X=pd.concat([X,smsData[new_features] ], axis=1, sort=False)
```

In [66]:
```python
# extracting the response variable
y=smsData['label']
```

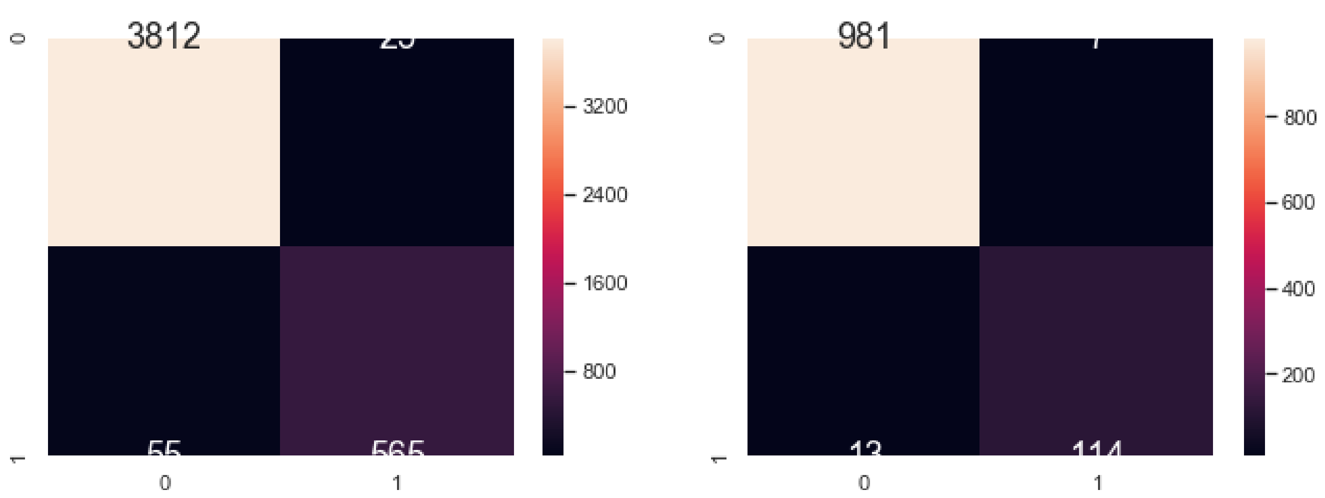
In [67]:
```python
# split into train and test sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

Classification models

decision tree model

In [330]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.tree import plot_tree

# training and fitting the model
dtClassifier=DecisionTreeClassifier(max_depth=3)
dtClassifier.fit(X_train,y_train)

# predicting train and test set
y_train_pred = dtClassifier.predict(X_train)
y_test_pred = dtClassifier.predict(X_test)

from sklearn.metrics import confusion_matrix
# Plot the Confusion Matrix for Train and Test
f, axes = plt.subplots(1, 2, figsize=(12, 4))
sb.heatmap(confusion_matrix(y_train, y_train_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[0])
sb.heatmap(confusion_matrix(y_test, y_test_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[1])
```

Out[330]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d4715d5ac8>
```



In [331]:
```python
def print_metrics(actual, predicted):
    from sklearn.metrics import confusion_matrix
    cm=confusion_matrix(actual, predicted)
    TN=cm[0][0]
    TP=cm[1][1]
    FP=cm[0][1]
    FN=cm[1][0]
    precision=TP/(FP+TP)
    recall=TP/(FN+TP)
    F1= 2*(recall * precision) / (recall + precision)
    accuracy=(TP+TN)/(TP+FP+FN+TN)
    print('{0:<15} {1}'.format("Accuracy:",accuracy))
    print('{0:<15} {1}'.format("Precision:",precision))
    print('{0:<15} {1}'.format("Recall:",recall))
    print('{0:<15} {1}'.format("F1:",F1))
```

- decision tree model performs very well in training set, over 89% for all metrics
- however, there is a slight drop of performance in the test set, likely an indication of OVERFITTING

In [332]:
```python
print("Performance on training set:")
print_metrics(y_train, y_train_pred)
print()
print("Performance on test set:")
print_metrics(y_test, y_test_pred)
```

```
Performance on training set:
Accuracy:       0.9820507067534215
Precision:      0.9576271186440678
Recall:         0.9112903225806451
F1:             0.9338842975206612

Performance on test set:
Accuracy:       0.9820627802690582
Precision:      0.9421487603305785
Recall:         0.8976377952755905
F1:             0.9193548387096775
```

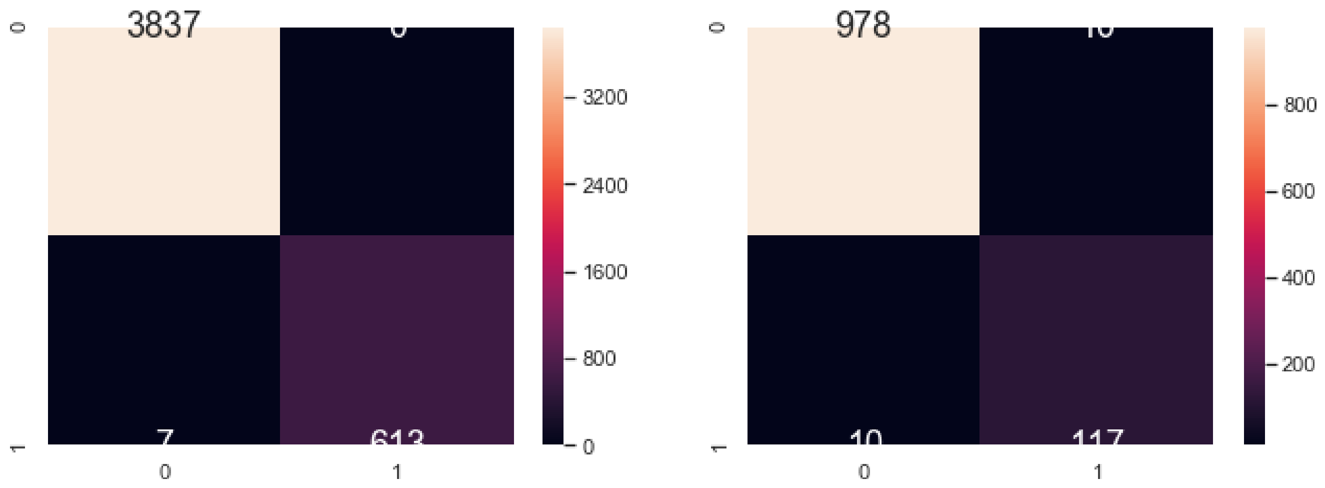
- plotting the tree, we see that num_of_digits, presence of link and presence of '..' are the most significant predictors

In [333]:
```python
# Plot the Decision Tree
# Import the function plot_tree
from sklearn.tree import plot_tree

# Plot the Decision Tree model
f, axes = plt.subplots(1, 1, figsize=(16, 12))

plot_tree(dtClassifier, filled=True, rounded = True,
          feature_names=pd.DataFrame(X_train).columns)
plt.show()
```

- let's increase the max_depth

In [334]:
```python
# training and fitting the model
dtClassifier=DecisionTreeClassifier(max_depth=20)
dtClassifier.fit(X_train,y_train)

# predicting train and test set
y_train_pred = dtClassifier.predict(X_train)
y_test_pred = dtClassifier.predict(X_test)

from sklearn.metrics import confusion_matrix
# Plot the Confusion Matrix for Train and Test
f, axes = plt.subplots(1, 2, figsize=(12, 4))
sb.heatmap(confusion_matrix(y_train, y_train_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[0])
sb.heatmap(confusion_matrix(y_test, y_test_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[1])
```

Out[334]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d418411648>
```



- with max_depth=20, performance in the training set is over 98% for all metrics
- however, there is OVERFITTING, because we see a drop in performance in the test set

In [335]:
```python
print("Performance on training set:")
print_metrics(y_train, y_train_pred)
print()
print("Performance on test set:")
print_metrics(y_test, y_test_pred)
```

```
Performance on training set:
Accuracy:       0.9984294368409243
Precision:      1.0
Recall:         0.9887096774193549
F1:             0.994322789943228

Performance on test set:
Accuracy:       0.9820627802690582
Precision:      0.9212598425196851
Recall:         0.9212598425196851
F1:             0.9212598425196851
```

random forest model

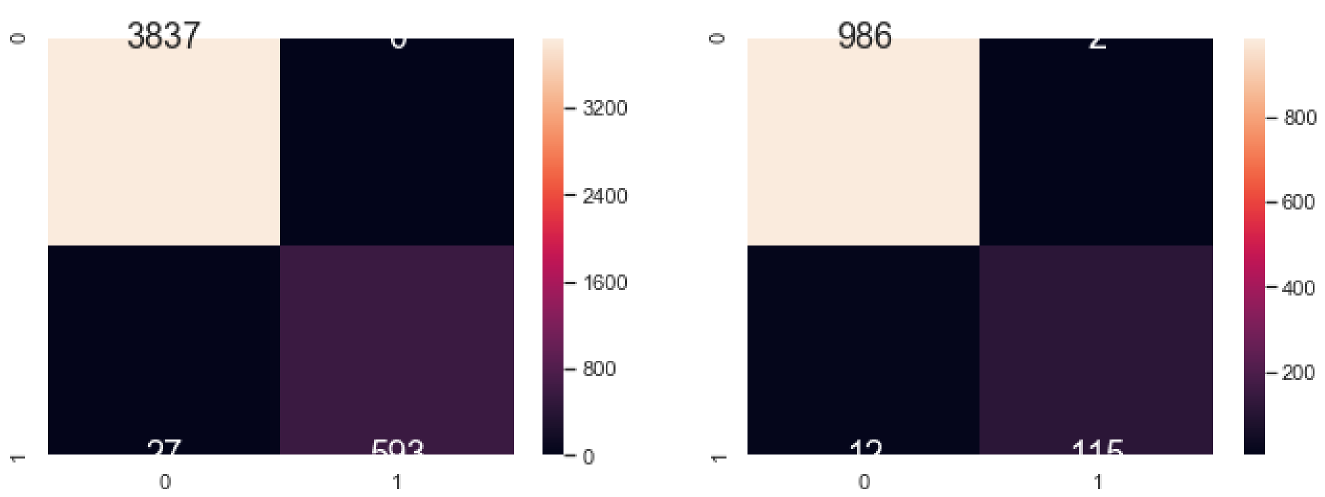
In [336]:
```python
# Import RandomForestClassifier model from Scikit-Learn
from sklearn.ensemble import RandomForestClassifier

# Create the Random Forest object
rforest = RandomForestClassifier(max_depth=20,n_estimators= 1000)

# Fit Random Forest on Train Data
rforest.fit(X_train, y_train.values.ravel())
```

Out[336]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=20, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=1000,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [337]:
```python
# predicting train and test set
y_train_pred = rforest.predict(X_train)
y_test_pred = rforest.predict(X_test)
```

In [338]:
```python
from sklearn.metrics import confusion_matrix
# Plot the Confusion Matrix for Train and Test
f, axes = plt.subplots(1, 2, figsize=(12, 4))
sb.heatmap(confusion_matrix(y_train, y_train_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[0])
sb.heatmap(confusion_matrix(y_test, y_test_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[1])
```

Out[338]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d41d9ca888>
```



- precision is very high, which is good because we don't want user emails to be falsely predicted as spam
- compared to decision tree performance did not drop as much, indicating less OVERFITTING
- recall in the test set is still at 90% so there are still 10% 'spam' not detected

In [339]:
```
print("Performance on training set:")
print_metrics(y_train, y_train_pred)
print()
print("Performance on test set:")
print_metrics(y_test, y_test_pred)
```

```
Performance on training set:
Accuracy:       0.9939421135292797
Precision:      1.0
Recall:         0.9564516129032258
F1:             0.9777411376751854

Performance on test set:
Accuracy:       0.9874439461883409
Precision:      0.9829059829059829
Recall:         0.905511811023622
F1:             0.9426229508196721
```

using GridSearch

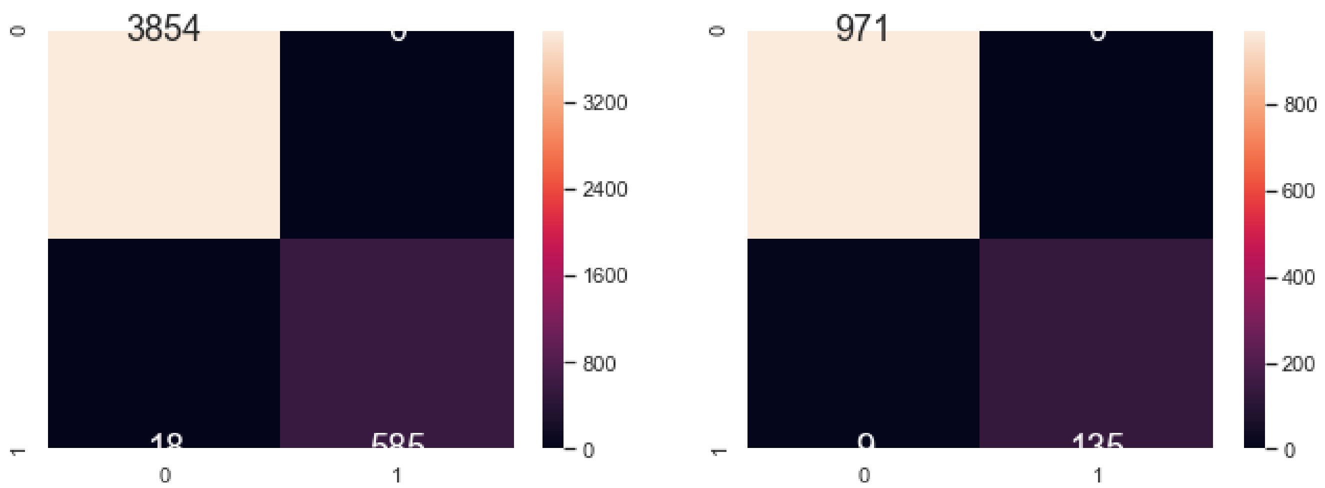
- best parameters for the random forest are as follows: {'max_depth': 25, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 500}

```
#data splitting
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

# Import RandomForestClassifier model from Scikit-Learn
from sklearn.ensemble import RandomForestClassifier

# Create the Random Forest object
rforest = RandomForestClassifier()

# set the maximum depth of each tree
n_estimators = [100, 300, 500, 800, 1200]
max_depth = [5, 8, 15, 25, 30]
min_samples_split = [2, 5, 10, 15, 100]
min_samples_leaf = [1, 2, 5, 10]
from sklearn.model_selection import GridSearchCV

hyperF = dict(n_estimators = n_estimators, max_depth = max_depth,
              min_samples_split = min_samples_split,
             min_samples_leaf = min_samples_leaf)

gridF = GridSearchCV(rforest, hyperF, cv = 3, verbose = 1,
                      n_jobs = -1)
bestF = gridF.fit(X_train, y_train)
bestF.best_params_
```

applying best parameters from gridSearch

```
In [340]: # split into train and test sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

# Import RandomForestClassifier model from Scikit-Learn
from sklearn.ensemble import RandomForestClassifier

# Create the Random Forest object
rforest = RandomForestClassifier(max_depth= 25,
                                 min_samples_leaf= 1,
                                 min_samples_split=2,
                                 n_estimators=500)

# Fit Random Forest on Train Data
rforest.fit(X_train, y_train.values.ravel())

# predicting train and test set
y_train_pred = rforest.predict(X_train)
y_test_pred = rforest.predict(X_test)

from sklearn.metrics import confusion_matrix
# Plot the Confusion Matrix for Train and Test
f, axes = plt.subplots(1, 2, figsize=(12, 4))
sb.heatmap(confusion_matrix(y_train, y_train_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[0])
sb.heatmap(confusion_matrix(y_test, y_test_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[1])
```

```
Out[340]: <matplotlib.axes._subplots.AxesSubplot at 0x1d41d97fa88>
```



- using the best parameters, we see an improvement in the recall compared to previous models

In [341]:
```
print("Performance on training set:")
print_metrics(y_train, y_train_pred)
print()
print("Performance on test set:")
print_metrics(y_test, y_test_pred)
```

```
Performance on training set:
Accuracy:       0.9959614090195199
Precision:      1.0
Recall:         0.9701492537313433
F1:             0.9848484848484849

Performance on test set:
Accuracy:       0.9919282511210762
Precision:      1.0
Recall:         0.9375
F1:             0.967741935483871
```

upsampling(disabled)

- SMOTE used instead

```
from sklearn.utils import resample


# concatenate our training data back together
X = pd.concat([X_train, y_train], axis=1)

# separate minority and majority classes
not_spam = X[X.label=='good']
spam = X[X.label=='spam']

# upsample minority
spam_upsampled = resample(spam,
                          replace=True, # sample with replacement
                          n_samples=len(not_spam), # match number in majority class
                          random_state=27) # reproducible results

# combine majority and upsampled minority
upsampled = pd.concat([not_spam, spam_upsampled])

# check new class counts
upsampled.label.value_counts()
```

```
# Import RandomForestClassifier model from Scikit-Learn
from sklearn.ensemble import RandomForestClassifier

# Create the Random Forest object
rforest = RandomForestClassifier(n_estimators  =500,  # n_estimators denote number of
trees
                                 max_depth = 10)
                                        # set the maximum depth of each tree

# trying logistic regression again with the balanced dataset
y_train = upsampled.label
X_train = upsampled.drop('label', axis=1)

# Fit Random Forest on Train Data
```

```
rforest.fit(X_train, y_train)

y_train_pred = rforest.predict(X_train)
y_test_pred = rforest.predict(X_test)

from sklearn.metrics import confusion_matrix


# Plot the Confusion Matrix for Train and Test
f, axes = plt.subplots(1, 2, figsize=(12, 4))
sb.heatmap(confusion_matrix(y_train, y_train_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[0])
sb.heatmap(confusion_matrix(y_test, y_test_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[1])

print("Performance on training set:")
print_metrics(y_train, y_train_pred)
print()
print("Performance on test set:")
print_metrics(y_test, y_test_pred)
```

SMOTE

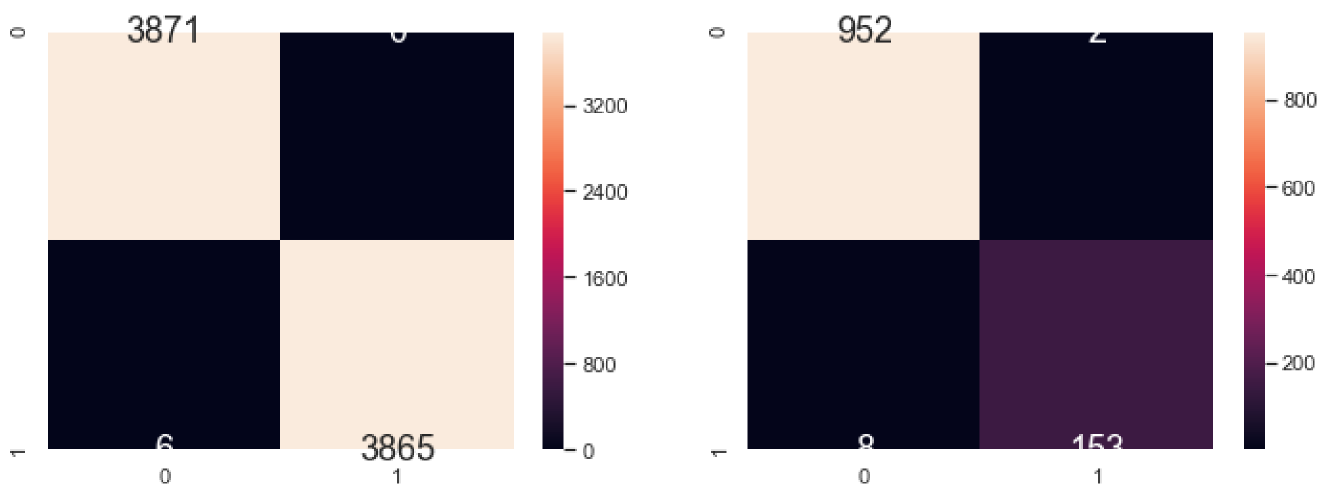
- A technique similar to upsampling is to create synthetic samples. Here we will use imblearn's SMOTE or Synthetic Minority Oversampling Technique. SMOTE uses a nearest neighbors algorithm to generate new and synthetic data we can use for training our model

In [68]:

```python
from imblearn.over_sampling import SMOTE

# split into train and test sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)

# Import RandomForestClassifier model from Scikit-Learn
from sklearn.ensemble import RandomForestClassifier

sm = SMOTE(random_state=20, ratio=1.0)
X_train, y_train = sm.fit_sample(X_train, y_train)

# using best parameters
rforest = RandomForestClassifier(max_depth= 25,
                                 min_samples_leaf= 1,
                                 min_samples_split=2,
                                 n_estimators=500)
# Fit Random Forest on Train Data
rforest.fit(X_train, y_train)

# making predictions
y_train_pred = rforest.predict(X_train)
y_test_pred = rforest.predict(X_test)

from sklearn.metrics import confusion_matrix
# Plot the Confusion Matrix for Train and Test
f, axes = plt.subplots(1, 2, figsize=(12, 4))
sb.heatmap(confusion_matrix(y_train, y_train_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[0])
sb.heatmap(confusion_matrix(y_test, y_test_pred),
           annot = True, fmt=".0f", annot_kws={"size": 18}, ax = axes[1])
```

Out[68]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d86c2d47c8>
```



In [70]:
```
pd.DataFrame(X_train)
```

Out[70]:

	0	1	2	3	4	5	6	7	8	9	...	289	290	291	292	293
0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	26.000000	1.000000	0.000000
1	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	160.000000	20.000000	15.000000
2	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	63.000000	1.000000	0.000000
3	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	158.000000	22.000000	23.000000
4	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	11.000000	1.000000	0.000000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7737	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	194.675637	18.046338	14.907325
7738	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	96.470816	5.509728	15.019456
7739	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	160.953626	11.721754	23.860877
7740	0.0	0.0	0.0	0.0	0.0	3.852497	0.0	0.0	0.0	0.0	...	0.0	0.0	151.481562	13.184379	18.963124
7741	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	157.508470	24.245765	29.508470

7742 rows × 299 columns

- using best parameters and smote metrics are over 96% on both sets
- there is the least drop in performance from training to test set compared to previous models

In [343]:
```
print("Performance on training set:")
print_metrics(y_train, y_train_pred)
print()
print("Performance on test set:")
print_metrics(y_test, y_test_pred)
```

```
Performance on training set:
Accuracy:       0.9984492116826054
Precision:      1.0
Recall:         0.9968984233652106
F1:             0.9984468030028475

Performance on test set:
Accuracy:       0.9901345291479821
Precision:      0.9625
Recall:         0.9685534591194969
F1:             0.9655172413793103
```

References

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- using .crosstab https://pandas.pydata.org/pandas-docs/version/0.23.4/generated/pandas.crosstab.html (https://pandas.pydata.org/pandas-docs/version/0.23.4/generated/pandas.crosstab.html)
- handling text data https://www.analyticsvidhya.com/blog/2018/02/the-different-methods-deal-text-data-predictive-python/ (https://www.analyticsvidhya.com/blog/2018/02/the-different-methods-deal-text-data-predictive-python/)
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