Identifying Duplicate Questions

Welcome to the Quora Question Pairs competition! Here, our goal is to identify which questions asked on Quora (https://www.quora.com/), a quasi-forum website with over 100 million visitors a month, are duplicates of questions that have already been asked. This could be useful, for example, to instantly provide answers to questions that have already been answered. We are tasked with predicting whether a pair of questions are duplicates or not, and submitting a binary prediction against the logloss metric.

If you have any questions or want to discuss competitions/hardware/games/anything with other Kagglers, then join the KaggleNoobs Slack channel here (https://goo.gl/gGWFXe). We also have regular AMAs with top Kagglers there.

And as always, if this helped you, some upvotes would be very much appreciated - that's where I get my motivation! :D

Let's dive right into the data!

In [1]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
import gc
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

pal = sns.color_palette()

print('# File sizes')
for f in os.listdir('../input'):
    if 'zip' not in f:
        print(f.ljust(30) + str(round(os.path.getsize('../input/' + f)
/ 1000000, 2)) + 'MB')
```

```
# File sizes
train.csv                     63.4MB
test.csv                      314.02MB
```

Looks like we are simply given two files this time round, one for the training set and one for the test set. They are relatively small compared to other recent competitions, weighing in at less than 400MB total.

It's worth noting that there is a lot more testing data than training data. This could be a sign that some of the test data is dummy data designed to deter hand-labelling, and not included in the calculations, like we recently saw in the DSTL competition (https://www.kaggle.com/c/dstl-satellite-imagery-feature-detection/leaderboard).

Let's open up one of the datasets.

Training set

In [2]:

```
df_train = pd.read_csv('../input/train.csv')
df_train.head()
```

Out[2]:

	id	qid1	qid2	question1	question2	is_duplicate
0	0	1	2	What is the step by step guide to invest in sh...	What is the step by step guide to invest in sh...	0
1	1	3	4	What is the story of Kohinoor (Koh-i-Noor) Dia...	What would happen if the Indian government sto...	0
2	2	5	6	How can I increase the speed of my internet co...	How can Internet speed be increased by hacking...	0
3	3	7	8	Why am I mentally very lonely? How can I solve...	Find the remainder when [math]23^{24}[/math] i...	0
4	4	9	10	Which one dissolve in water quikly sugar, salt...	Which fish would survive in salt water?	0

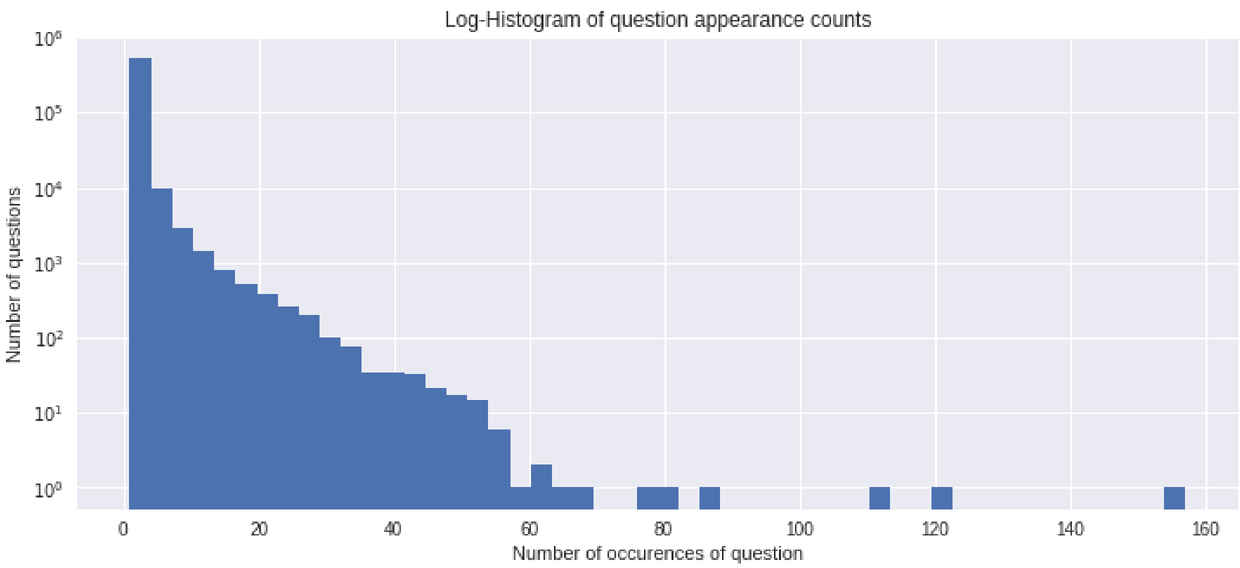
We are given a minimal number of data fields here, consisting of:

`id` **:** Looks like a simple rowID
`qid{1, 2}` **:** The unique ID of each question in the pair
`question{1, 2}` **:** The actual textual contents of the questions.
`is_duplicate` **:** The **label** that we are trying to predict - whether the two questions are duplicates of each other.

In [3]:

```
print('Total number of question pairs for training: {}'.format(len(df_
train)))
print('Duplicate pairs:
{}%'.format(round(df_train['is_duplicate'].mean()*100, 2)))
qids = pd.Series(df_train['qid1'].tolist() + df_train['qid2'].tolist
())
print('Total number of questions in the training data: {}'.format(len(
    np.unique(qids))))
print('Number of questions that appear multiple times: {}'.format(np.su
m(qids.value_counts() > 1)))

plt.figure(figsize=(12, 5))
plt.hist(qids.value_counts(), bins=50)
plt.yscale('log', nonposy='clip')
plt.title('Log-Histogram of question appearance counts')
plt.xlabel('Number of occurences of question')
plt.ylabel('Number of questions')
print()
```

```
Total number of question pairs for training: 404290
Duplicate pairs: 36.92%
Total number of questions in the training data: 537933
Number of questions that appear multiple times: 111780
```



In terms of questions, everything looks as I would expect here. Most questions only appear a few times, with very few questions appearing several times (and a few questions appearing many times). One question appears more than 160 times, but this is an outlier.

We can see that we have a 37% positive class in this dataset. Since we are using the LogLoss (https://www.kaggle.com/wiki/LogarithmicLoss) metric, and LogLoss looks at the actual predicts as opposed to the order of predictions, we should be able to get a decent score by creating a submission predicting the mean value of the label.

Test Submission

In [4]:

```
from sklearn.metrics import log_loss

p = df_train['is_duplicate'].mean() # Our predicted probability
print('Predicted score:', log_loss(df_train['is_duplicate'], np.zeros_l
ike(df_train['is_duplicate']) + p))

df_test = pd.read_csv('../input/test.csv')
sub = pd.DataFrame({'test_id': df_test['test_id'], 'is_duplicate': p})
sub.to_csv('naive_submission.csv', index=False)
sub.head()
```

```
Predicted score: 0.658527383984
```

Out[4]:

	is_duplicate	test_id
0	0.369198	0
1	0.369198	1
2	0.369198	2
3	0.369198	3
4	0.369198	4

0.55 on the leaderboard! Score!

However, not all is well. The discrepancy between our local score and the LB one indicates that the distribution of values on the leaderboard is very different to what we have here, which could cause problems with validation later on in the competition.

According to this excellent notebook by David Thaler (www.kaggle.com/davidthaler/quora-question-pairs/how-many-1-s-are-in-the-public-lb/notebook), using our score and submission we can calculate that we have about 16.5% positives in the test set. This is quite surprising to see, so it'll be something that will need to be taken into account in machine learning models.

Next, I'll take a quick peek at the statistics of the test data before we look at the text itself.

Test Set

In [5]:

```
df_test = pd.read_csv('../input/test.csv')
df_test.head()
```

Out[5]:

	test_id	question1	question2
0	0	How does the Surface Pro himself 4 compare wit...	Why did Microsoft choose core m3 and not core ...
1	1	Should I have a hair transplant at age 24? How...	How much cost does hair transplant require?
2	2	What but is the best way to send money from Ch...	What you send money to China?
3	3	Which food not emulsifiers?	What foods fibre?
4	4	How "aberystwyth" start reading?	How their can I start reading?

In [6]:

```
print('Total number of question pairs for testing: {}'.format(len(df_te
st)))
```

```
Total number of question pairs for testing: 2345796
```

Nothing out of the ordinary here. We are once again given rowIDs and the textual data of the two questions. It is worth noting that we are not given question IDs here however for the two questions in the pair.

It is also worth pointing out that the actual number of test rows are likely to be much lower than 2.3 million. According to the data page (https://www.kaggle.com/c/quora-question-pairs/data), most of the rows in the test set are using auto-generated questions to pad out the dataset, and deter any hand-labelling. This means that the true number of rows that are scored could be very low.

We can actually see in the head of the test data that some of the questions are obviously auto-generated, as we get delights such as "How their can I start reading?" and "What foods fibre?". Truly insightful questions.

Now onto the good stuff - the text data!

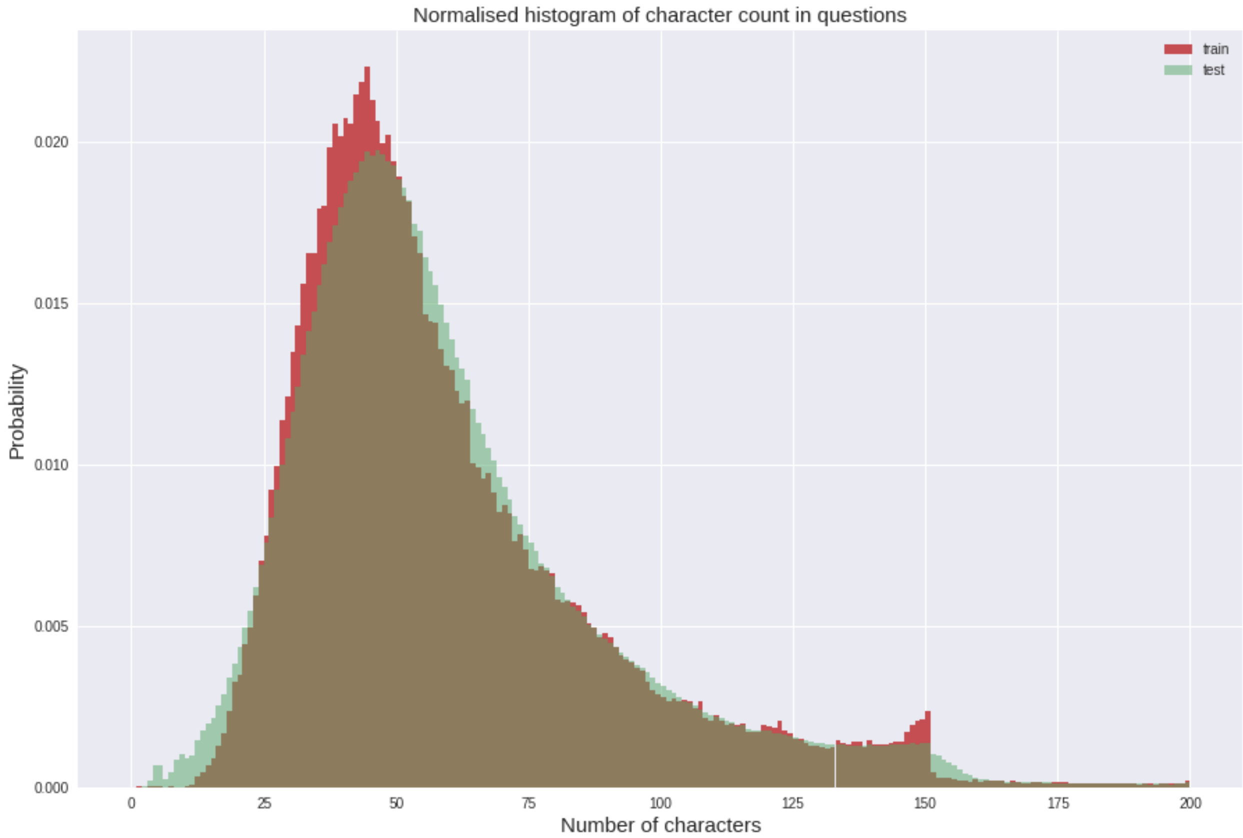
Text analysis

First off, some quick histograms to understand what we're looking at. **Most analysis here will be only on the training set, to avoid the auto-generated questions**

In [7]:

```
train_qs = pd.Series(df_train['question1'].tolist() + df_train['questi
on2'].tolist()).astype(str)
test_qs = pd.Series(df_test['question1'].tolist() + df_test['question
2'].tolist()).astype(str)

dist_train = train_qs.apply(len)
dist_test = test_qs.apply(len)
plt.figure(figsize=(15, 10))
plt.hist(dist_train, bins=200, range=[0, 200], color=pal[2], normed=Tr
ue, label='train')
plt.hist(dist_test, bins=200, range=[0, 200], color=pal[1], normed=Tru
e, alpha=0.5, label='test')
plt.title('Normalised histogram of character count in questions', fonts
ize=15)
plt.legend()
plt.xlabel('Number of characters', fontsize=15)
plt.ylabel('Probability', fontsize=15)

print('mean-train {:.2f} std-train {:.2f} mean-test {:.2f} std-test
{:.2f} max-train {:.2f} max-test {:.2f}'.format(dist_train.mean(),
                          dist_train.std(), dist_test.mean(), dist_test
.std(), dist_train.max(), dist_test.max()))
```

```
mean-train 59.82 std-train 31.96 mean-test 60.07 std-test 31.62 max-tr
ain 1169.00 max-test 1176.00
```



We can see that most questions have anywhere from 15 to 150 characters in them. It seems that the test distribution is a little different from the train one, but not too much so (I can't tell if it is just the larger data reducing noise, but it also seems like the distribution is a lot smoother in the test set).

One thing that catches my eye is the steep cut-off at 150 characters for the training set, for most questions, while the test set slowly decreases after 150. Could this be some sort of Quora question size limit?

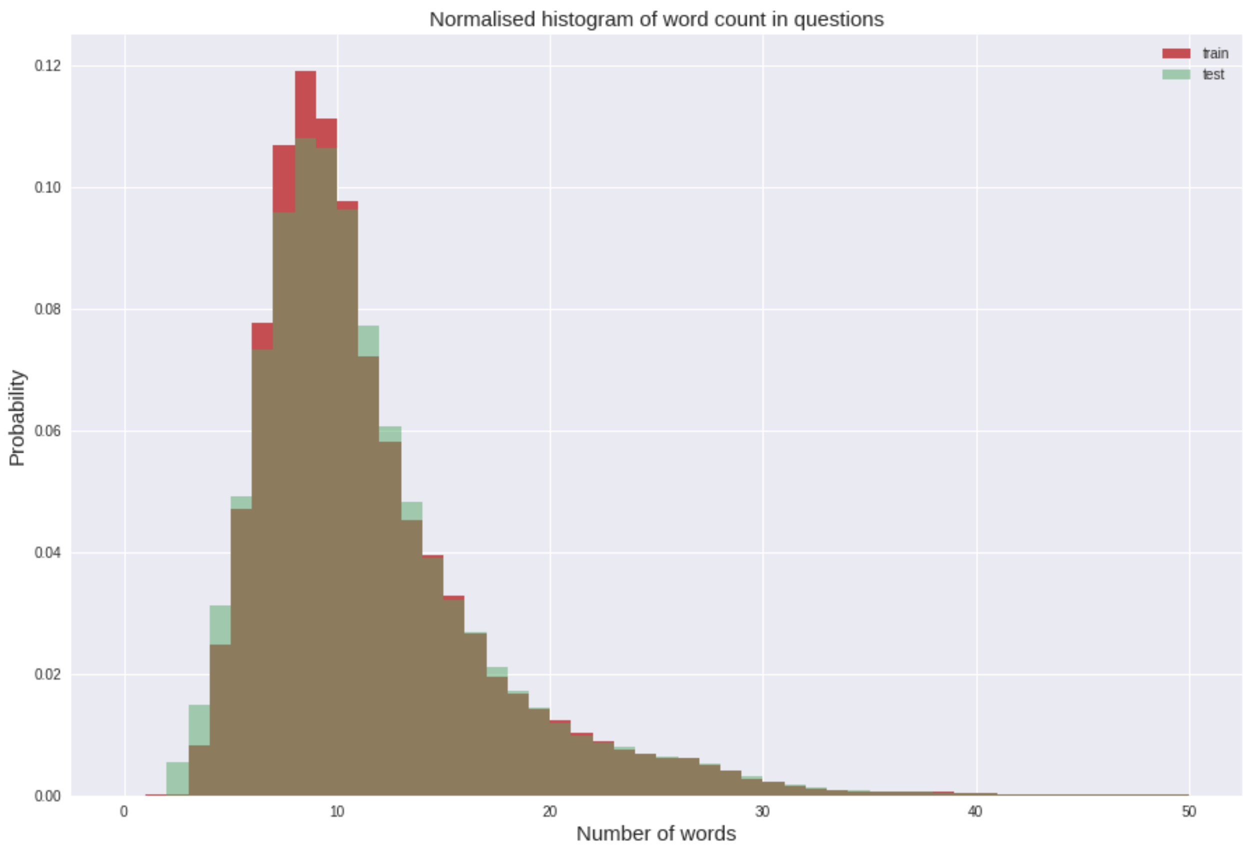
It's also worth noting that I've truncated this histogram at 200 characters, and that the max of the distribution is at just under 1200 characters for both sets - although samples with over 200 characters are very rare.

Let's do the same for word count. I'll be using a naive method for splitting words (splitting on spaces instead of using a serious tokenizer), although this should still give us a good idea of the distribution.

In [8]:

```
dist_train = train_qs.apply(lambda x: len(x.split(' ')))
dist_test = test_qs.apply(lambda x: len(x.split(' ')))

plt.figure(figsize=(15, 10))
plt.hist(dist_train, bins=50, range=[0, 50], color=pal[2], normed=True
, label='train')
plt.hist(dist_test, bins=50, range=[0, 50], color=pal[1], normed=True,
alpha=0.5, label='test')
plt.title('Normalised histogram of word count in questions', fontsize=1
5)
plt.legend()
plt.xlabel('Number of words', fontsize=15)
plt.ylabel('Probability', fontsize=15)

print('mean-train {:.2f} std-train {:.2f} mean-test {:.2f} std-test
{:.2f} max-train {:.2f} max-test {:.2f}'.format(dist_train.mean(),
                          dist_train.std(), dist_test.mean(), dist_test
.std(), dist_train.max(), dist_test.max()))
```

```
mean-train 11.06 std-train 5.89 mean-test 11.02 std-test 5.84 max-trai
n 237.00 max-test 238.00
```



We see a similar distribution for word count, with most questions being about 10 words long. It looks to me like the distribution of the training set seems more "pointy", while on the test set it is wider. Nevertheless, they are quite similar.

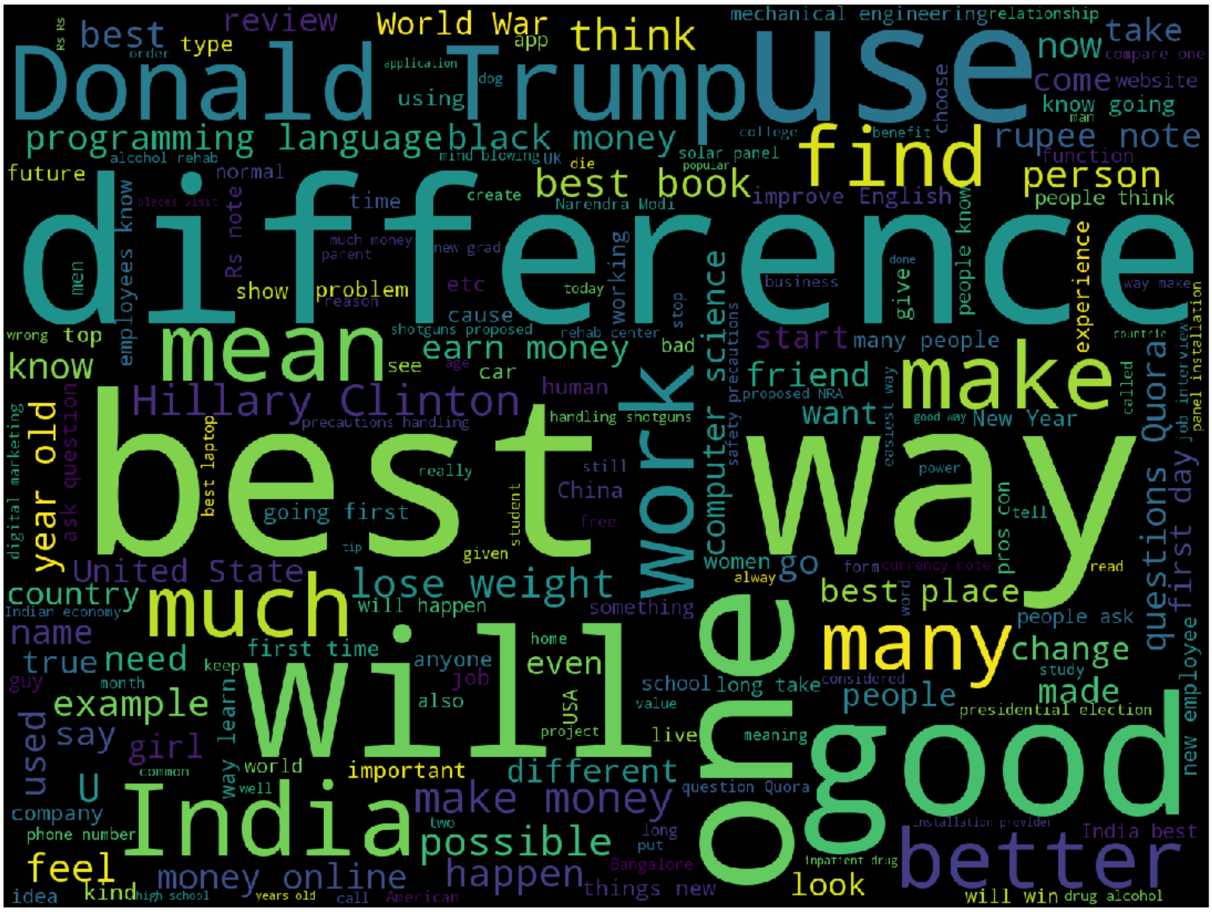
So what are the most common words? Let's take a look at a word cloud.

In [9]:

```
from wordcloud import WordCloud
cloud = WordCloud(width=1440, height=1080).generate(" ".join(train_qs.
astype(str)))
plt.figure(figsize=(20, 15))
plt.imshow(cloud)
plt.axis('off')
```

Out[9]:

```
(-0.5, 1439.5, 1079.5, -0.5)
```



Semantic Analysis

Next, I will take a look at usage of different punctuation in questions - this may form a basis for some interesting features later on.

In [10]:

```
qmarks = np.mean(train_qs.apply(lambda x: '?' in x))
math = np.mean(train_qs.apply(lambda x: '[math]' in x))
fullstop = np.mean(train_qs.apply(lambda x: '.' in x))
capital_first = np.mean(train_qs.apply(lambda x: x[0].isupper()))
capitals = np.mean(train_qs.apply(lambda x: max([y.isupper() for y in
x])))
numbers = np.mean(train_qs.apply(lambda x: max([y.isdigit() for y in x
])))

print('Questions with question marks: {:.2f}%'.format(qmarks * 100))
print('Questions with [math] tags: {:.2f}%'.format(math * 100))
print('Questions with full stops: {:.2f}%'.format(fullstop * 100))
print('Questions with capitalised first letters: {:.2f}%'.format(capita
l_first * 100))
print('Questions with capital letters: {:.2f}%'.format(capitals *
100))
print('Questions with numbers: {:.2f}%'.format(numbers * 100))
```

```
Questions with question marks: 99.87%
Questions with [math] tags: 0.12%
Questions with full stops: 6.31%
Questions with capitalised first letters: 99.81%
Questions with capital letters: 99.95%
Questions with numbers: 11.83%
```

Initial Feature Analysis

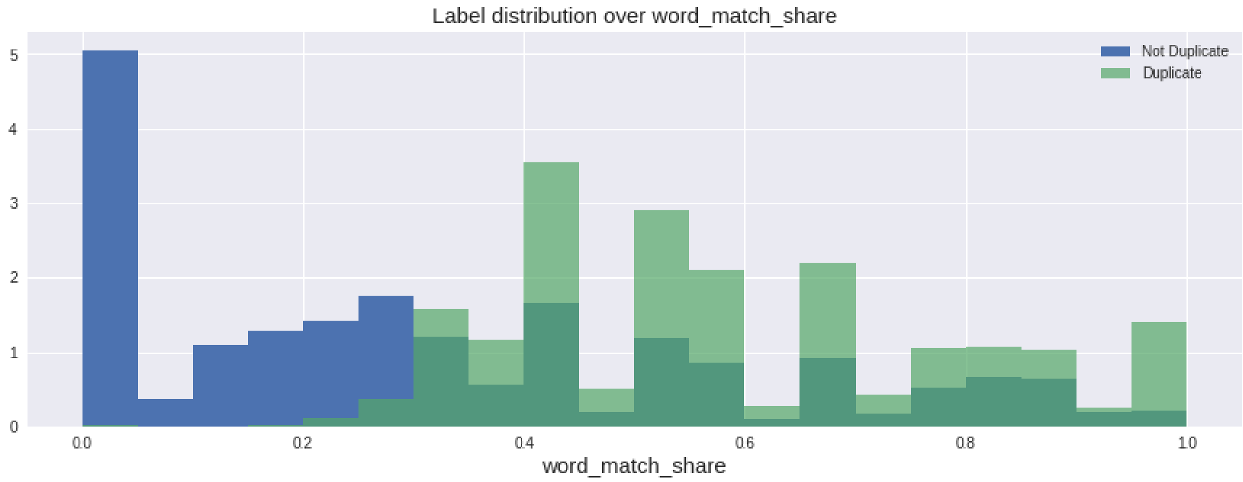
Before we create a model, we should take a look at how powerful some features are. I will start off with the word share feature from the benchmark model.

In [11]:

```
from nltk.corpus import stopwords

stops = set(stopwords.words("english"))

def word_match_share(row):
    q1words = {}
    q2words = {}
    for word in str(row['question1']).lower().split():
        if word not in stops:
            q1words[word] = 1
    for word in str(row['question2']).lower().split():
        if word not in stops:
            q2words[word] = 1
    if len(q1words) == 0 or len(q2words) == 0:
        # The computer-generated chaff includes a few questions that are nothing but stopwords
        return 0
    shared_words_in_q1 = [w for w in q1words.keys() if w in q2words]
    shared_words_in_q2 = [w for w in q2words.keys() if w in q1words]
    R = (len(shared_words_in_q1) + len(shared_words_in_q2))/(len(q1words) + len(q2words))
    return R

plt.figure(figsize=(15, 5))
train_word_match = df_train.apply(word_match_share, axis=1, raw=True)
plt.hist(train_word_match[df_train['is_duplicate'] == 0], bins=20, normed=True, label='Not Duplicate')
plt.hist(train_word_match[df_train['is_duplicate'] == 1], bins=20, normed=True, alpha=0.7, label='Duplicate')
plt.legend()
plt.title('Label distribution over word_match_share', fontsize=15)
plt.xlabel('word_match_share', fontsize=15)
```

Out[11]:

```
<matplotlib.text.Text at 0x7f11740696d8>
```



Here we can see that this feature has quite a lot of predictive power, as it is good at separating the duplicate questions from the non-duplicate ones. Interestingly, it seems very good at identifying questions which are definitely different, but is not so great at finding questions which are definitely duplicates.

TF-IDF

I'm now going to try to improve this feature, by using something called TF-IDF (term-frequency-inverse-document-frequency). This means that we weigh the terms by how **uncommon** they are, meaning that we care more about rare words existing in both questions than common one. This makes sense, as for example we care more about whether the word "exercise" appears in both than the word "and" - as uncommon words will be more indicative of the content.

You may want to look into using sklearn's TfidfVectorizer (http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html) to compute weights if you are implementing this yourself, but as I am too lazy to read the documentation I will write a version in pure python with a few changes which I believe should help the score.

In [12]:

```
from collections import Counter

# If a word appears only once, we ignore it completely (likely a typo)
# Epsilon defines a smoothing constant, which makes the effect of extrem
ely rare words smaller
def get_weight(count, eps=10000, min_count=2):
    if count < min_count:
        return 0
    else:
        return 1 / (count + eps)

eps = 5000
words = (" ".join(train_qs)).lower().split()
counts = Counter(words)
weights = {word: get_weight(count) for word, count in counts.items()}
```

In [13]:

```
print('Most common words and weights: \n')
print(sorted(weights.items(), key=lambda x: x[1] if x[1] > 0 else 9999
)[:10])
print('\nLeast common words and weights: ')
(sorted(weights.items(), key=lambda x: x[1], reverse=True)[:10])
```

```
Most common words and weights:

[('the', 2.5891040146646852e-06), ('what', 3.115623919267953e-06), ('i
s', 3.5861702928825277e-06), ('how', 4.366449945201053e-06), ('i', 4.4
805878531263305e-06), ('a', 4.540645588989843e-06), ('to', 4.671434644
293609e-06), ('in', 4.884625153865692e-06), ('of', 5.920242493132519e-
06), ('do', 6.070908207867897e-06)]

Least common words and weights:
```

Out[13]:

```
[('シ', 9.998000399920016e-05),
 ('し?', 9.998000399920016e-05),
 ('19-year-old.', 9.998000399920016e-05),
 ('1-855-425-3768', 9.998000399920016e-05),
 ('confederates', 9.998000399920016e-05),
 ('asahi', 9.998000399920016e-05),
 ('fab', 9.998000399920016e-05),
 ('109?', 9.998000399920016e-05),
 ('samrudi', 9.998000399920016e-05),
 ('fulfill?', 9.998000399920016e-05)]
```

In [14]:

```
def tfidf_word_match_share(row):
    q1words = {}
    q2words = {}
    for word in str(row['question1']).lower().split():
        if word not in stops:
            q1words[word] = 1
    for word in str(row['question2']).lower().split():
        if word not in stops:
            q2words[word] = 1
    if len(q1words) == 0 or len(q2words) == 0:
        # The computer-generated chaff includes a few questions that are
nothing but stopwords
        return 0

    shared_weights = [weights.get(w, 0) for w in q1words.keys() if w i
n q2words] + [weights.get(w, 0) for w in q2words.keys() if w in q1word
s]
    total_weights = [weights.get(w, 0) for w in q1words] + [weights.ge
t(w, 0) for w in q2words]

    R = np.sum(shared_weights) / np.sum(total_weights)
    return R
```

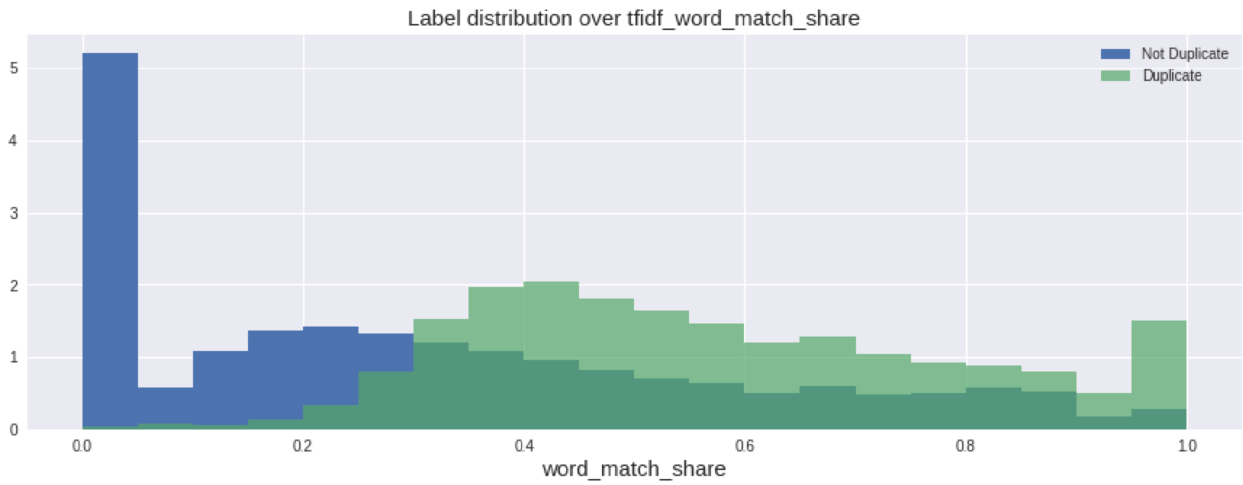
In [15]:

```
plt.figure(figsize=(15, 5))
tfidf_train_word_match = df_train.apply(tfidf_word_match_share, axis=1,
raw=True)
plt.hist(tfidf_train_word_match[df_train['is_duplicate'] == 0].fillna(
0), bins=20, normed=True, label='Not Duplicate')
plt.hist(tfidf_train_word_match[df_train['is_duplicate'] == 1].fillna(
0), bins=20, normed=True, alpha=0.7, label='Duplicate')
plt.legend()
plt.title('Label distribution over tfidf_word_match_share', fontsize=15
)
plt.xlabel('word_match_share', fontsize=15)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:17: Runti
meWarning: invalid value encountered in double_scalars
```

Out[15]:

```
<matplotlib.text.Text at 0x7f114ce4b668>
```



In [16]:

```
from sklearn.metrics import roc_auc_score
print('Original AUC:', roc_auc_score(df_train['is_duplicate'], train_wo
rd_match))
print('   TFIDF AUC:', roc_auc_score(df_train['is_duplicate'], tfidf_tr
ain_word_match.fillna(0)))
```

```
Original AUC: 0.780553200628
   TFIDF AUC: 0.77056466105
```

So it looks like our TF-IDF actually got *worse* in terms of overall AUC, which is a bit disappointing. (I am using the AUC metric since it is unaffected by scaling and similar, so it is a good metric for testing the predictive power of individual features.

However, I still think that this feature should provide some extra information which is not provided by the original feature. Our next job is to combine these features and use it to make a prediction. For this, I will use our old friend XGBoost to make a classification model.

Rebalancing the Data

However, before I do this, I would like to rebalance the data that XGBoost receives, since we have 37% positive class in our training data, and only 17% in the test data. By re-balancing the data so our training set has 17% positives, we can ensure that XGBoost outputs probabilities that will better match the data on the leaderboard, and should get a better score (since LogLoss looks at the probabilities themselves and not just the order of the predictions like AUC)

In [17]:

```
# First we create our training and testing data
x_train = pd.DataFrame()
x_test = pd.DataFrame()
x_train['word_match'] = train_word_match
x_train['tfidf_word_match'] = tfidf_train_word_match
x_test['word_match'] = df_test.apply(word_match_share, axis=1, raw=True)
x_test['tfidf_word_match'] = df_test.apply(tfidf_word_match_share, axis=1, raw=True)

y_train = df_train['is_duplicate'].values
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:17: RuntimeWarning: invalid value encountered in double_scalars
/opt/conda/lib/python3.6/site-packages/ipykernel/__main__.py:17: RuntimeWarning: invalid value encountered in long_scalars
```

In [18]:

```
pos_train = x_train[y_train == 1]
neg_train = x_train[y_train == 0]

# Now we oversample the negative class
# There is likely a much more elegant way to do this...
p = 0.165
scale = ((len(pos_train) / (len(pos_train) + len(neg_train))) / p) - 1
while scale > 1:
    neg_train = pd.concat([neg_train, neg_train])
    scale -=1
neg_train = pd.concat([neg_train, neg_train[:int(scale * len(neg_train
))]])
print(len(pos_train) / (len(pos_train) + len(neg_train)))

x_train = pd.concat([pos_train, neg_train])
y_train = (np.zeros(len(pos_train)) + 1).tolist() + np.zeros(len(neg_t
rain)).tolist()
del pos_train, neg_train
```

```
0.19124366100096607
```

In [19]:

```
# Finally, we split some of the data off for validation
from sklearn.cross_validation import train_test_split

x_train, x_valid, y_train, y_valid = train_test_split(x_train, y_train,
test_size=0.2, random_state=4242)
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:43:
DeprecationWarning: This module was deprecated in version 0.18 in favo
r of the model_selection module into which all the refactored classes
and functions are moved. Also note that the interface of the new CV it
erators are different from that of this module. This module will be re
moved in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

XGBoost

Now we can finally run XGBoost on our data, in order to see the score on the leaderboard!

In [20]:

```
import xgboost as xgb

# Set our parameters for xgboost
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
params['max_depth'] = 4

d_train = xgb.DMatrix(x_train, label=y_train)
d_valid = xgb.DMatrix(x_valid, label=y_valid)

watchlist = [(d_train, 'train'), (d_valid, 'valid')]

bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds
=50, verbose_eval=10)
```

```
[0]     train-logloss:0.683189  valid-logloss:0.683238
Multiple eval metrics have been passed: 'valid-logloss' will be used f
or early stopping.

Will train until valid-logloss hasn't improved in 50 rounds.
[10]    train-logloss:0.602041  valid-logloss:0.602515
[20]    train-logloss:0.544863  valid-logloss:0.545663
[30]    train-logloss:0.503151  valid-logloss:0.504194
[40]    train-logloss:0.471989  valid-logloss:0.473231
[50]    train-logloss:0.448341  valid-logloss:0.449746
[60]    train-logloss:0.430164  valid-logloss:0.431706
[70]    train-logloss:0.416072  valid-logloss:0.417726
[80]    train-logloss:0.405012  valid-logloss:0.406775
[90]    train-logloss:0.396327  valid-logloss:0.398177
[100]   train-logloss:0.389488  valid-logloss:0.391404
[110]   train-logloss:0.384071  valid-logloss:0.386038
[120]   train-logloss:0.379786  valid-logloss:0.381792
[130]   train-logloss:0.376375  valid-logloss:0.378414
[140]   train-logloss:0.373661  valid-logloss:0.375724
[150]   train-logloss:0.371482  valid-logloss:0.373567
[160]   train-logloss:0.369728  valid-logloss:0.371835
[170]   train-logloss:0.368327  valid-logloss:0.370453
[180]   train-logloss:0.367186  valid-logloss:0.369324
[190]   train-logloss:0.366276  valid-logloss:0.368424
[200]   train-logloss:0.365539  valid-logloss:0.367697
[210]   train-logloss:0.364945  valid-logloss:0.367108
[220]   train-logloss:0.364443  valid-logloss:0.366615
[230]   train-logloss:0.364033  valid-logloss:0.366215
[240]   train-logloss:0.363691  valid-logloss:0.365883
[250]   train-logloss:0.363389  valid-logloss:0.3656
[260]   train-logloss:0.363117  valid-logloss:0.365335
[270]   train-logloss:0.362879  valid-logloss:0.365108
[280]   train-logloss:0.362655  valid-logloss:0.364893
[290]   train-logloss:0.362455  valid-logloss:0.364698
[300]   train-logloss:0.362288  valid-logloss:0.36454
[310]   train-logloss:0.362151  valid-logloss:0.364412
[320]   train-logloss:0.362029  valid-logloss:0.364298
[330]   train-logloss:0.361896  valid-logloss:0.364174
[340]   train-logloss:0.361792  valid-logloss:0.364075
[350]   train-logloss:0.361691  valid-logloss:0.363984
[360]   train-logloss:0.361568  valid-logloss:0.36387
[370]   train-logloss:0.361455  valid-logloss:0.363768
[380]   train-logloss:0.361353  valid-logloss:0.363673
```

```
[390]	train-logloss:0.361258	valid-logloss:0.363586
[399]	train-logloss:0.361186	valid-logloss:0.363524
```

In [21]:

```
d_test = xgb.DMatrix(x_test)
p_test = bst.predict(d_test)

sub = pd.DataFrame()
sub['test_id'] = df_test['test_id']
sub['is_duplicate'] = p_test
sub.to_csv('simple_xgb.csv', index=False)
```

0.35460 on the leaderboard - a good first score!