In [1]:

```
import requests
from IPython.core.display import HTML
styles = requests.get("https://raw.githubusercontent.com/Harvard
-IACS/2018-CS109A/master/content/styles/cs109.css").text
HTML(styles)

import pandas as pd
import numpy as np

%matplotlib inline
```

Fixing Redirects

We load in the raw dataset of wikipedia pages that contain information about the page.

In [2]:

```
wikipages = pd.read_csv('../data/raw/enwiki_20190801.page.csv')
```

In [3]:

```
wikipages.head()
```

Out[3]:

	page_id	page_title	page_is_redirect	page_len	wikidata
0	31880	Universe	0	125156	1.0
1	24437894	Boston	0	188674	100.0
2	12027	Gabon	0	60678	1000.0
3	1313683	Dutch_Wikipedia	0	8325	10000.0
4	4037258	Cadier_en_Keer	0	2584	100000.(

In [4]:

```
wikipages.shape
```

Out[4]:

```
(14730178, 6)
```

We noticed that in the raw dataset, 8.7 million pages do not have corresponding wikidata_numeric_ids! This didn't sound right at all. However, we noticed that many pages that are redirect pages do not have a corresponding wikidata_numeric_id.

In [5]:

```
wikipages.wikidata_numeric_id.isnull().sum()
```

Out[5]:

```
8718368
```

We noticed that many pages that are redirect pages do not have a corresponding wikidata_numeric_id.

In [6]:

```
wikipages[wikipages.page_is_redirect == 1].tail()
```

Out[6]:

	page_id	pa
14730173	24181285	Est.Domain
14730174	18236087	.p3t
14730175	7358181	Ceti_Alpha_Six
14730176	215608	Pascals_Wager
14730177	49820527	Swimming_at_the_2005_World_Aquatics_Cham

We load in the raw dataset about redirect pages to further investigate. Indeed, we see that while these redirect pages (source pages) do not have a corresponding wikidata_numeric_id, the pages they redirect to (target pages) do.

In [7]:

```
redirect = pd.read_csv('../data/raw/enwiki_20190801.redirect.csv
')
```

In [8]:

```
redirect.head()
```

Out[8]:

	source_page_id	target_page_id	so
0	39378878	38421275	Infocom_Network
1	25917412	2238902	Canyonero_(car)
2	3245614	1941596	Chief_Dull_Knife
3	43321056	32960669	National_Register_of_Historic_Pla
4	13307706	369596	The_New_York_Botanical_Garde

In [9]:

```
#Example of source page not having a wikidata_numeric_id but a t
arget page does.
wikipages[wikipages.page_id == redirect[redirect.source_page_id
== 24181285]['target_page_id'].iloc[0]]
```

Out[9]:

	page_id	page_title	page_is_redirect	page_len	wikida
3839571	24179837	EstDomains	0	6606	53999

We also see examples where a target page not having a wikidata_numeric_id, but one of their source pages does.

In [10]:

```
wikipages[wikipages.page_id == 325726.0]
```

Out[10]:

	page_id	page_title	page_is_redirect	page_
6040736	325726	Social_network_analysis	0	47818

In [11]:

```
#All source pages of this target page
redirect[redirect['target_page_id'] == 325726]
```

Out[11]:

	source_page_id	target_page_id	source_
1717720	1559348	325726	Social_Network_Analysis
1721329	12567496	325726	Social_networking_potent
1722555	20645616	325726	Cascade_(Social_Network
1724358	17661070	325726	Social_Network_Change_
1727934	17576720	325726	Social_network_change_
1730560	39596224	325726	Networks_in_Political_Sci
1732941	14825621	325726	Social_Networking_Poten

In [12]:

```
#This source page does not have wikidata_numeric_id
wikipages[wikipages.page_id == 1559348]
```

Out[12]:

	page_id	page_title	page_is_redirect	page
7291787	1559348	Social_Network_Analysis	1	102

In [13]:

```
#But this source page does
wikipages[wikipages.page_id == 17576720]
```

Out[13]:

	page_id	page_title	page_is_redi
5421981	17576720	Social_network_change_detection	1

Thus, we need to link these problematic source/target pages with the wikidata_numeric_id of their target/source pages.

In [14]:

```
#This code cell fixes the problematic behavior mentioned.

wikipages_cleaned = wikipages.copy()
#Get target page id for all
target_page_ids = wikipages_cleaned.merge(redirect[['source_page
_id', 'target_page_id']],
                                          how = 'left', left_on = ['page_id'], r
ight_on = ['source_page_id'])
#Pages that do not appear in redirect have both source_page_id a
nd target_page_id as null after join. These are just page_id for
both
target_page_ids['target_page_id'] = target_page_ids['target_page
_id'].fillna(target_page_ids['page_id'])
target_page_ids['source_page_id'] = target_page_ids['source_page
_id'].fillna(target_page_ids['page_id'])
```

```
target_page_ids = target_page_ids.drop(['page_id'], axis = 1)


wikipages_cleaned = target_page_ids.merge(wikipages[['page_id',
'page_title', 'wikidata_numeric_id']], how = 'left',
                                          left_on = ['target_pag
e_id'], right_on = ['page_id'])

wikipages_cleaned['wikidata_numeric_id_x'] = wikipages_cleaned['
wikidata_numeric_id_x'].fillna(
                                                    wikipages_cl
eaned['wikidata_numeric_id_y'])
wikipages_cleaned = wikipages_cleaned.drop(['wikidata_numeric_id
_y', 'page_id'], axis = 1)
wikipages_cleaned = wikipages_cleaned.rename(columns = {'page_ti
tle_x': 'page_title',
                                                        'page_ti
tle_y': 'target_page_title',
                                                        'wikidat
a_numeric_id_x': 'wikidata_numeric_id',
                                                        'source_
page_id': 'page_id'
                                                       })
#There are some instances of source page having wikidata instead
of target.
#Set target page to have source page wikidata for those
wikidata_ids = wikipages_cleaned.groupby(['target_page_id'])[['w
ikidata_numeric_id']].min().reset_index()
wikipages_cleaned = wikipages_cleaned.merge(wikidata_ids, how =
'left', on = ['target_page_id'])
wikipages_cleaned['wikidata_numeric_id_x'] = wikipages_cleaned['
wikidata_numeric_id_x'].fillna(
                                                    wikipages_cl
eaned['wikidata_numeric_id_y'])
wikipages_cleaned = wikipages_cleaned.drop(['wikidata_numeric_id
_y'], axis = 1)
wikipages_cleaned = wikipages_cleaned.rename(columns = {'wikidat
a_numeric_id_x': 'wikidata_numeric_id'})
```

Now only 40k pages have missing wikidata_numeric_id!

In [15]:

```
wikipages_cleaned.wikidata_numeric_id.isnull().sum()
```

Out[15]:

```
40693
```

75% of the articles still without wikidata item have fewer than 10 views. As such, most of these pages are insignificant and should pose no problem to our analysis.

In [16]:

```
wikipages_cleaned[wikipages_cleaned.wikidata_numeric_id.isnull()
]['views'].describe()
```

Out[16]:

```
count    40693.000000
mean        34.924090
std        407.577772
min          0.000000
25%          0.000000
50%          0.000000
75%         10.000000
max      50810.000000
Name: views, dtype: float64
```

Exploration of Knowledge Graph

Next, we explore the raw Wikidata knowledge graph.

In [17]:

```
triplets = pd.read_csv('../data/raw/wikidata_20190805.qpq_item_s
tatements.csv')
```

In [18]:

```
triplets.head()
```

Out[18]:

	source_item_id	edge_property_id	target_item_id	el_rank
0	31	1344	1088364	1
1	31	1151	3247091	1
2	31	1546	1308013	1
3	31	5125	7112200	1
4	31	38	4916	0

In [19]:

```
entities = pd.read_csv('../data/raw/wikidata_20190805.item.csv')
```

In [20]:

```
entities.head()
```

Out[20]:

	id	en_label	en_description	enwiki_title
0	51475818	YouTube as a source of information on kidney s...	scientific article published on 4 December 2010	NaN
1	51475821	The sinus lift with phycogenic bone substitute...	scientific article published in June 2005	NaN
2	51475829	Economic aspects of single-tooth replacement.	scientific article published in June 2005	NaN
3	51475835	Template:Peace, Unity, and Development Party/m...	NaN	Template:Peace, Unity, and Development Party/m...
4	51475865	Long-term results and survival rate of implant...	scientific article published in June 2005	NaN

Looking at the outdegree summary statistics, we see that 75% of entities have 5 or fewer edges going out. However, at the same time, we see that the max is quite large with 8319 degrees!

In [21]:

```
out_degree = triplets.groupby(['source_item_id'])[['source_item_
id']].count()
out_degree = out_degree.rename(columns={"source_item_id": "out_d
egree"})
out_degree = out_degree.reset_index()
out_degree = out_degree.sort_values('out_degree', ascending = Fa
lse)
```

In [22]:

```
out_degree['out_degree'].describe()
```

Out[22]:

```
count    5.641113e+07
mean     6.793780e+00
std      1.339614e+01
min      1.000000e+00
25%      2.000000e+00
50%      3.000000e+00
75%      5.000000e+00
max      8.319000e+03
Name: out_degree, dtype: float64
```

Looking at the top out degree entities, we see that many of them come from scholarly articles, with many biology/medicine related. Indeed, the highest degree entity, `BayGenomics: a resource of insertional mutations in mouse embryonic stem cells` has an edge to every cell line mentioned!

In [23]:

```
top_out_degree = out_degree.iloc[:10]
```

In [24]:

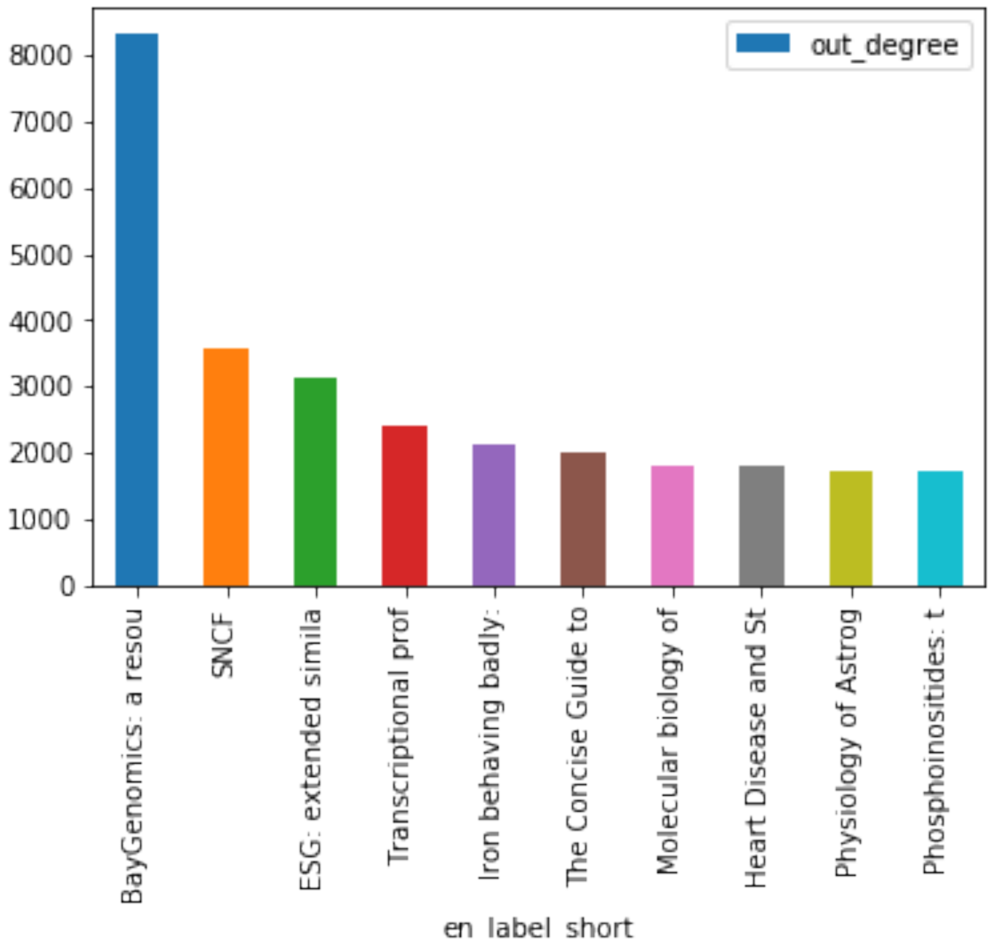
```
top_out_degree = top_out_degree.merge(entities, left_on = ['sour
ce_item_id'], right_on = ['id'])
```

In [25]:

```
top_out_degree['en_label_short'] = top_out_degree['en_label'].st
r[:20]
```

In [26]:

```
top_out_degree.plot.bar(x = 'en_label_short', y = 'out_degree');
```



We see a similar story for indegree: 75% of entities have 9 or fewer edges going in. The max indegree is almost 22 million!

In [27]:

```
in_degree = triplets.groupby(['target_item_id'])[['target_item_i
d']].count()
in_degree = in_degree.rename(columns={"target_item_id": "in_degr
ee"})
in_degree = in_degree.reset_index()
in_degree = in_degree.sort_values('in_degree', ascending = False
)
```

The highest indegree entity is scholarly article!

In [28]:

```
top_in_degree = in_degree.iloc[:10]
```

In [29]:

```
top_in_degree = top_in_degree.merge(entities, left_on = ['target
_item_id'], right_on = ['id'])
```

In [30]:

```
top_in_degree
```

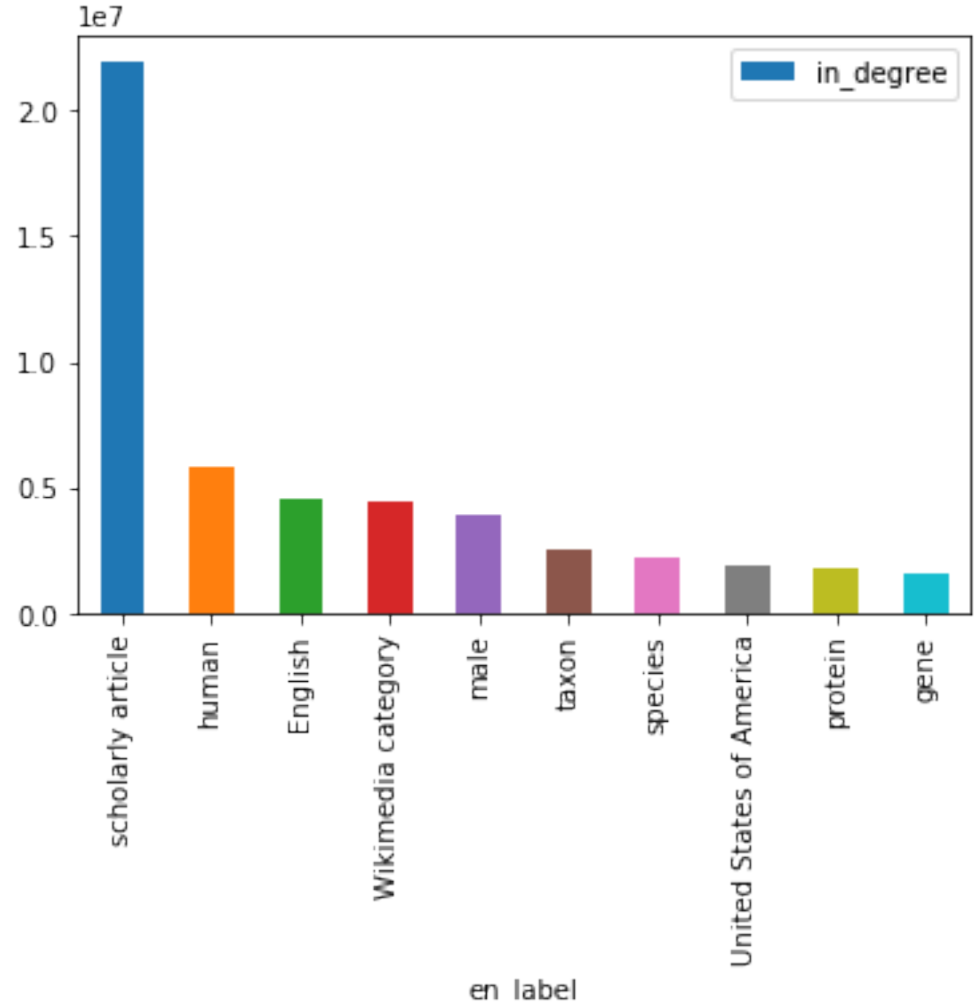
Out[30]:

	target_item_id	in_degree	id	en_label	en_description
0	13442814	21910388	13442814	scholarly article	article in an academic publication, usually pe...
1	5	5837659	5	human	common name of Homo sapiens, unique extant spe...
2	1860	4600258	1860	English	West Germanic language originating in England ...
3	4167836	4465143	4167836	Wikimedia category	use with 'instance of' (P31) for Wikimedia cat...
4	6581097	3913958	6581097	male	human who is male (use with P21)

5	16521	2596501	16521	taxon	group of one or more organism(s), which a taxo...
6	7432	2198219	7432	species	one of the basic units of biological classific...
7	30	1968964	30	United States of America	federal republic in North America
8	8054	1801629	8054	protein	biological molecule consisting of chains of am...
9	7187	1609904	7187	gene	basic physical and functional unit of heredity

In [31]:

```
top_in_degree.plot.bar(x = 'en_label', y = 'in_degree');
```



In [32]:

```
in_degree['in_degree'].describe()
```

Out[32]:

```
count    2.189076e+07
mean     1.750715e+01
std      5.276517e+03
min      1.000000e+00
25%      1.000000e+00
50%      3.000000e+00
75%      9.000000e+00
max      2.191039e+07
Name: in_degree, dtype: float64
```

From exploration of the full graph we see that it would not be computationally feasible to use the full graph. As such we made a smaller graph consisting of only relations between wikipedia pages.

NER Displacy

An example of NER with entities tagged.

In [33]:

```
import spacy
from spacy import displacy

ner = spacy.load('en_core_web_sm')
sample_text = "Apple Inc. is an American multinational technolog
y company headquartered in Cupertino, California, that designs,
develops, and sells consumer electronics, computer software, and
online services. It is considered one of the Big Four tech compa
nies along with Amazon, Google, and Facebook. The company's hard
ware products include the iPhone smartphone, the iPad tablet com
puter, the Mac personal computer, the iPod portable media player
, the Apple Watch smartwatch, the Apple TV digital media player,
the AirPods wireless earbuds and the HomePod smart speaker."
displacy.render(ner(sample_text), jupyter=True, style='ent')
```

Apple Inc. **ORG** is an American **NORP** multinational technology company headquartered in Cupertino **GPE** , California **GPE** , that designs, develops, and sells consumer electronics, computer software, and online services. It is considered one of the Big Four **CARDINAL** tech companies along with Amazon **ORG** , Google **ORG** , and Facebook **PERSON** . The company's hardware products include the iPhone **ORG** smartphone, the iPad tablet computer, the Mac **ORG** personal computer, the iPod portable media player, the Apple Watch **ORG** smartwatch, the Apple TV **ORG** digital media player, the AirPods **ORG** wireless earbuds anc the HomePod **PERSON** smart speaker.

Node2vec Graph Embeddings

In deep learning approaches, it would be helpful to represent our knowledge graphs in a continuous vector space. After doing a review of graph embeddings approaches, node2vec seemed like a reasonable method. In short, node2vec uses a random walk to traverse the graph to learn the embeddings. Each node is then represented as a vector. In particular, this approach is useful as it allows us to balance the trade-off between capturing the local information in a graph and the global structure of the knowledge graph.

In [34]:

```
from gensim.models import Word2Vec
model = Word2Vec.load('../data/graph_embedding_100000.model')

wikidata = pd.read_csv('../data/wikipages_cleaned.csv')
wikidata.dropna(inplace=True)
```

In [35]:

```
def id_title(data, idx):
    """Given a wikidata ID, extract the title"""
    return data[data['wikidata_numeric_id']==int(idx)]['target_p
age_title'].iloc[0]
```

Graph embedding of 100000 Wikidata entries projected onto 2 dimensions through PCA. This captures the structure and topology of the knowledge graph in 2D. If we plot the graph in plotly, we can see pockets of nodes which make sense. For example, countries are close to each other.

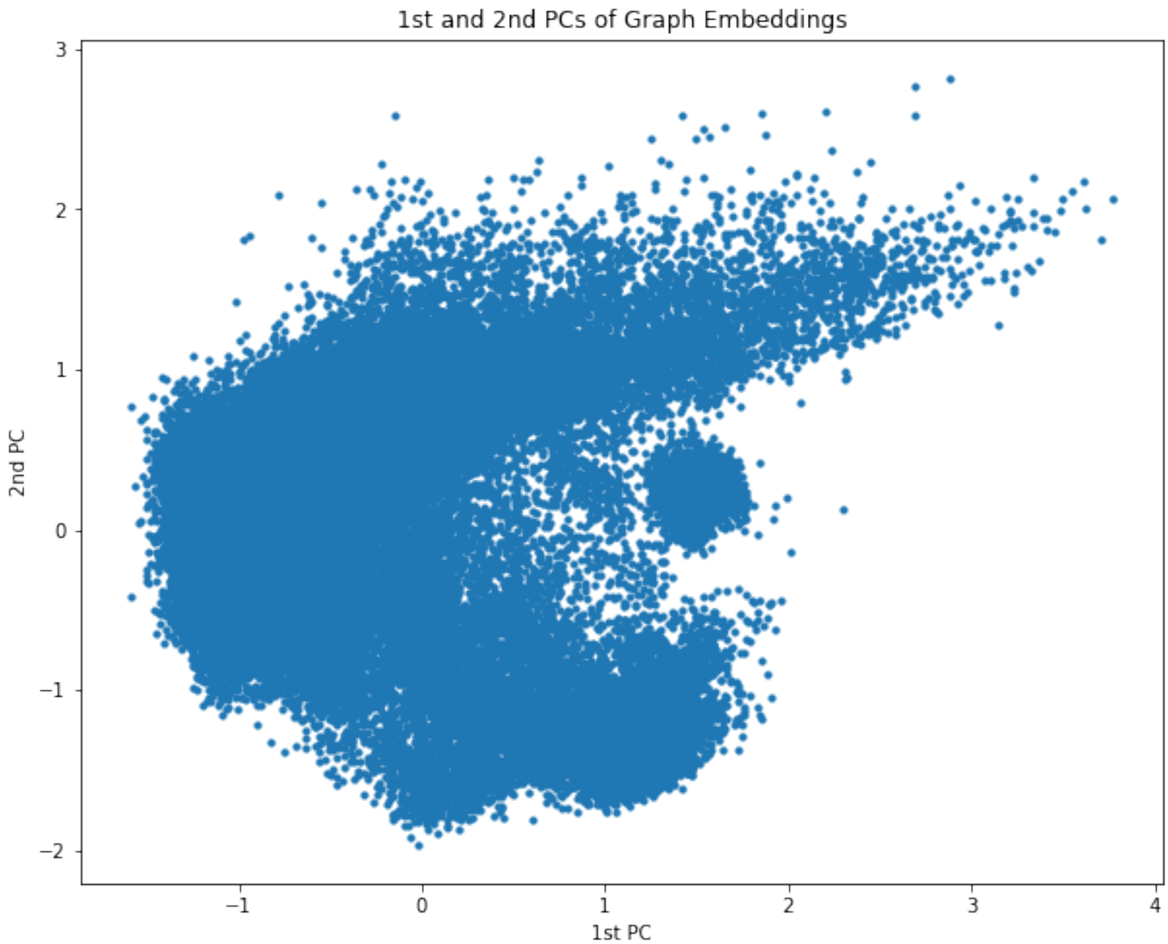
In [37]:

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# embedding for wikidata ID
X = model[model.wv.vocab]
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
plotly_X = pd.DataFrame(X_pca, columns=['1st PC', '2nd PC'])
plotly_X['titles'] = [id_title(wikidata, idx) for idx in list(mo
del.wv.vocab)]

plt.figure(figsize=(10,8))
plt.scatter(plotly_X['1st PC'], plotly_X['2nd PC'], s=10)
plt.title('1st and 2nd PCs of Graph Embeddings')
plt.xlabel('1st PC')
plt.ylabel('2nd PC');
```

```
/home/matteo/.local/lib/python3.7/site-packages/ipyk
ernel_launcher.py:5: DeprecationWarning: Call to dep
recated `__getitem__` (Method will be removed in 4.0
.0, use self.wv.__getitem__() instead).
  """
```



Word2Vec Entity Text Embeddings

We also did a simple word2vec text embedding on the named entities from NER (5000 Wikipedia text articles). We similarly did a PCA and captured the 1st 2 PCs in a scatterplot. Due to the lower number of entities, the locations of the entities do not seem to be as useful as the graph embeddings.

In [41]:

```
entity_model = Word2Vec.load('../data/entity_embedding.model')
```

In [42]:

```
# embedding for wikidata ID
X_entity = entity_model[entity_model.wv.vocab]
pca_entity = PCA(n_components=2)
X_pca_entity = pca_entity.fit_transform(X_entity)
plotly_X_entity = pd.DataFrame(X_pca_entity, columns=['1st PC',
'2nd PC'])
plotly_X_entity['entities'] = list(entity_model.wv.vocab)

plt.figure(figsize=(10,8))
plt.scatter(plotly_X_entity['1st PC'], plotly_X_entity['2nd PC']
, s=10)
plt.title('1st and 2nd PCs of Entity Text Embeddings')
plt.xlabel('1st PC')
plt.ylabel('2nd PC');
```

```
/home/matteo/.local/lib/python3.7/site-packages/ipyk
ernel_launcher.py:2: DeprecationWarning: Call to dep
recated `__getitem__` (Method will be removed in 4.0
.0, use self.wv.__getitem__() instead).
```