Hearthstone Cluster Project - KMeans Clustering

This project aims to use clustering algorithms on the Hearthstone decks data from Hearthpwn. In this notebook, the clustering algorithm of choice is KMeans Clustering.
The data is obtained from history of hearthstone hosted on Kaggle [here (https://www.kaggle.com/romainvincent/history-of-hearthstone)](https://www.kaggle.com/romainvincent/history-of-hearthstone)
History of Hearthstone dataset is scraped by the Kaggle user "romainvincent" roughly two years ago.

Introduction and background

Hearthstone is an online trading card game where players build a deck of 30 cards and face each other. The quality of the deck heavily depends on the synergy of the cards included within the deck. Various classes and synergies availble at the players' disposal gives rise to numerous deck archetypes. These archetypes are essentially different types of decks with different win conditions or the gameplan to defeat the opponent. The cards that synergize with each other form a group of cards that if they were to be included in a deck, they have to be included togehter. This is generally known as a **pcakage**.
This notebook aims to explore and surface these synergies through the decklist dataset.

Approach and methodology

Each row of the data is a deck that has been posted on hearthpwn. For each deck, there are 30 cards and their card ID ("dbfId") are recorded under the columns "card_0" to "card_29". First, the 30 card columns have to be combined into one single column with all the 30 IDs of the cards within a deck. Then, a column is created for each card. If a deck contains a particular card, the value under the column of that particular card will the count of the copies of the card within the deck.
For example, if deck number 10 has 2 copies of card 111, the value under the column "111" for deck 10 will be 2.

Importing packages

In [76]:
```
from collections import Counter
import json
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
```

Loading data

In [77]:
```python
refs = json.load(open("./history-of-hearthstone/refs.json"))
decks_data = pd.read_csv("./history-of-hearthstone/data.csv")
```

In [78]:
```python
# taking a look at the head
decks_data.head()
```

Out[78]:

	craft_cost	date	deck_archetype	deck_class	deck_format	deck_id	deck_set	deck_type	ra
0	9740	2016-02-19	Unknown	Priest	W	433004	Explorers	Tavern Brawl	
1	9840	2016-02-19	Unknown	Warrior	W	433003	Explorers	Ranked Deck	
2	2600	2016-02-19	Unknown	Mage	W	433002	Explorers	Theorycraft	
3	15600	2016-02-19	Unknown	Warrior	W	433001	Explorers	None	
4	7700	2016-02-19	Unknown	Paladin	W	432997	Explorers	Ranked Deck	

5 rows × 41 columns

Data cleaning

Data types of the columns

Column card_0 to card_29 are of the same type - int.

In [79]:
```python
decks_data.dtypes[1:13]
```

Out[79]:
```
date              object
deck_archetype    object
deck_class        object
deck_format       object
deck_id            int64
deck_set          object
deck_type         object
rating             int64
title             object
user              object
card_0             int64
card_1             int64
dtype: object
```

The column "date" is not of the correct type. Changing the column datatype to datetime.

In [80]:
```python
decks_data['date'] = pd.to_datetime(decks_data['date'])
```

In [81]:
```
decks_data.dtypes[1:13]
```

Out[81]:
```
date              datetime64[ns]
deck_archetype            object
deck_class                object
deck_format               object
deck_id                    int64
deck_set                  object
deck_type                 object
rating                     int64
title                     object
user                      object
card_0                     int64
card_1                     int64
dtype: object
```

Replacing nulls under "title" with a dummy deck name

In [82]:
```
decks_data.isnull().sum()[decks_data.isnull().sum() != 0]
```

Out[82]:
```
title    8
dtype: int64
```

There are 8 decks without title. Filling the null titles with a placeholder name

In [83]:
```
decks_data = decks_data.fillna('some deck')
```

Exploring the number of decks by type and format

Total number of decks in both Wild and Standard format

In [84]:
```
decks = len(decks_data)
print ('Number of decks :', decks)
```

```
Number of decks : 346232
```

Total wild decks

In [85]:
```
wild = len(decks_data[decks_data['deck_format'] == 'W'])
print ('Wild decks:', wild)
```

```
Wild decks: 175446
```

Count of all decks by type

In [86]:
```
decks_data['deck_type'].value_counts()
```

Out[86]:
```
Ranked Deck      202375
None              91058
Theorycraft       19688
Arena             14095
PvE Adventure      9059
Tavern Brawl       6360
Tournament         3597
Name: deck_type, dtype: int64
```

Count of *standard* decks by type

In [87]:
```
decks_data[decks_data['deck_format'] != 'W']['deck_type'].value_counts()
```

Out[87]:
```
Ranked Deck      101431
None              47837
Theorycraft        9644
Arena              7233
Tournament         2460
PvE Adventure      1398
Tavern Brawl        783
Name: deck_type, dtype: int64
```

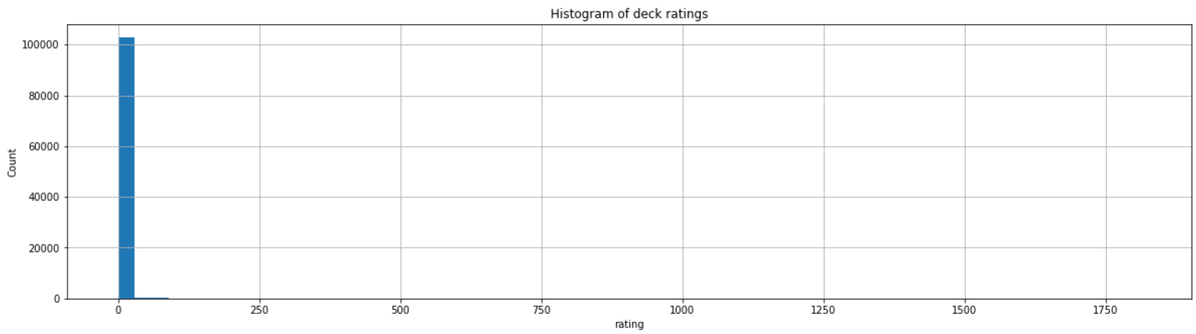
Choosing only *standard* ranked and tournament decks.

In [88]:
```
standard_decks = decks_data[decks_data['deck_format'] == 'S']
standard_decks = standard_decks[standard_decks['deck_type'].isin(['Ranked Dec
k', 'Tournament'])]
standard_decks['deck_type'].value_counts()
```

Out[88]:
```
Ranked Deck    101431
Tournament       2460
Name: deck_type, dtype: int64
```

Histogram of the rating

In [89]:
```
plt.figure(figsize=(20,5))
plt.hist(standard_decks['rating'], bins=60)
plt.title("Histogram of deck ratings")
plt.ylabel("Count")
plt.xlabel("rating")
plt.grid(True)
plt.show()
```



Decks with very low rating absolutely dominates the population. These decks are unlikely to be representative of the good decks that utilize package synergy too. As such, decks with low ratings are to be filtered.

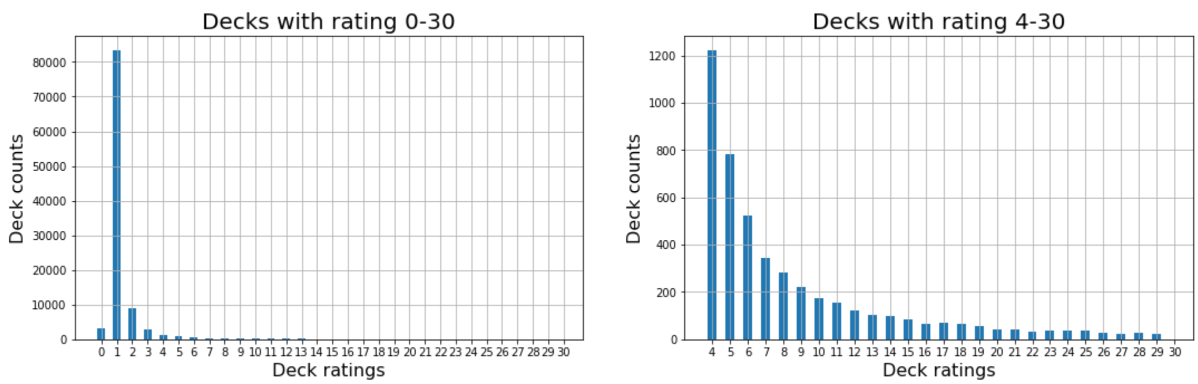
Examining the decks with low rating

(rating between 0-30)

In [90]:

```
low_ratings = standard_decks[standard_decks['rating'] < 31]
print(low_ratings['deck_type'].value_counts())

f, (ax1, ax2) = plt.subplots(1, 2, sharey=False, figsize=(18, 5))
ax1.hist(low_ratings['rating'], bins=np.arange(31)-0.25, width=0.5)
ax1.grid()
ax1.set_xticks(range(0,31))
ax1.set_title("Decks with rating 0-30", fontsize=20)
ax1.set_xlabel("Deck ratings", fontsize=16)
ax1.set_ylabel("Deck counts", fontsize=16);

ax2.hist(low_ratings[low_ratings['rating'] > 3]['rating'], bins=np.arange(4,31
)-0.25, width=0.5)
ax2.grid()
ax2.set_xticks(range(4,31))
ax2.set_title("Decks with rating 4-30", fontsize=20)
ax2.set_xlabel("Deck ratings", fontsize=16)
ax2.set_ylabel("Deck counts", fontsize=16);
```

```
Ranked Deck    100472
Tournament       2431
Name: deck_type, dtype: int64
```



The population of decks appear to be less skewed at rating value > 20. Hence, only decks with rating > 20 are considered in this study.
Looking at rated decks' columns.

Feature Engineering

Creating the "card" columns

First, the card IDs from card_0 to card_29 need to be combined into one space separated sentence to later generate the card counts for each card in a deck.

In [91]:
```
rated_decks = standard_decks[standard_decks['rating'] > 20].copy()
rated_decks.columns
```

Out[91]:
```
Index(['craft_cost', 'date', 'deck_archetype', 'deck_class', 'deck_format',
       'deck_id', 'deck_set', 'deck_type', 'rating', 'title', 'user', 'card_
0',
       'card_1', 'card_2', 'card_3', 'card_4', 'card_5', 'card_6', 'card_7',
       'card_8', 'card_9', 'card_10', 'card_11', 'card_12', 'card_13',
       'card_14', 'card_15', 'card_16', 'card_17', 'card_18', 'card_19',
       'card_20', 'card_21', 'card_22', 'card_23', 'card_24', 'card_25',
       'card_26', 'card_27', 'card_28', 'card_29'],
      dtype='object')
```

In [92]:
```
# Adding the first card to the "card" column. The first card is card_0.
rated_decks.loc[:, 'card'] = rated_decks.loc[:, 'card_0'].astype(int).astype(s
tr)

# for card_1 to card_29, concatenate the card ID to the existing 'card' colum
n.
for i in range(1,30):
    colname = 'card_' + str(i)
    rated_decks.loc[:, 'card'] = rated_decks.loc[:, 'card'] + ' ' + rated_deck
s[colname].astype(int).astype(str)
```

In [93]:
```
# checking the head of the dataframe
rated_decks["card"].head()
```

Out[93]:
```
137     180 180 306 459 461 461 559 573 667 667 749 82...
1690    64 64 95 137 137 254 254 734 825 825 1035 1124...
2414    28 28 1007 1007 242 304 304 401 401 511 511 53...
3527    296 296 437 437 519 699 141 1003 1003 1093 124...
3992    36 64 64 95 95 137 137 254 254 503 503 825 825...
Name: card, dtype: object
```

In [94]:
```python
# column "card" generated successfully. Dropping card_0 to card_29 columns.
rated_decks.drop(['card_0',
       'card_1', 'card_2', 'card_3', 'card_4', 'card_5', 'card_6', 'card_7',
       'card_8', 'card_9', 'card_10', 'card_11', 'card_12', 'card_13',
       'card_14', 'card_15', 'card_16', 'card_17', 'card_18', 'card_19',
       'card_20', 'card_21', 'card_22', 'card_23', 'card_24', 'card_25',
       'card_26', 'card_27', 'card_28', 'card_29'], axis=1, inplace=True)
rated_decks.head()
```

Out[94]:

	craft_cost	date	deck_archetype	deck_class	deck_format	deck_id	deck_set	deck_type
137	8120	2016-02-19	Miracle Rogue	Rogue	S	432773	Explorers	Ranked Deck
1690	8180	2016-04-21	Ramp Druid	Druid	S	478188	Explorers	Ranked Deck
2414	1680	2016-04-30	Unknown	Warrior	S	520990	Old Gods	Ranked Deck
3527	1860	2016-04-30	Midrange Hunter	Hunter	S	520585	Old Gods	Ranked Deck
3992	8260	2016-06-27	Yogg Druid	Druid	S	579170	Old Gods	Ranked Deck

The column "card" now contains 30 card IDs for the cards within the deck.

Creating columns containing the counts of each card

Cards details from JSON

JSON file contains the names and IDs of all the cards. This JSON file will be used to obtain the list of all card IDs.

In [95]:

```
card_data = pd.DataFrame.from_records(refs)

# dropping cards without dbfId
card_data = card_data[~card_data['dbfId'].isna()]

# casting the dbfId to integer instead of float
card_data['dbfId'] = card_data['dbfId'].astype(int)

card_data.head()
```

Out[95]:

	artist	attack	cardClass	collectible	cost	dbfId	flavor	health	id	name
0	Jakub Kasper	4.0	NEUTRAL	True	4.0	2518	The crowd ALWAYS yells lethal.	4.0	AT_121	Crowd Favorite
1	NaN	4.0	NEUTRAL	NaN	6.0	1769	NaN	7.0	CRED_09	Ben Thompson
2	NaN	NaN	NEUTRAL	NaN	NaN	10081	NaN	NaN	TB_007e	Deviate Switch
3	Mauricio Herrera	3.0	WARRIOR	True	3.0	40569	"I don't know a lot about used GvG cards, so I...	3.0	CFM_755	Grimestreet Pawnbroker
4	Ittoku	2.0	NEUTRAL	True	4.0	1370	His dreams of flying and breathing fire like h...	7.0	CS2_119	Oasis Snapjaw

5 rows × 32 columns

In [96]:
```
# reading the column names
card_data.columns
```

Out[96]:
```
Index(['artist', 'attack', 'cardClass', 'collectible', 'cost', 'dbfId',
       'flavor', 'health', 'id', 'name', 'playerClass', 'rarity',
       'referencedTags', 'set', 'text', 'type', 'elite', 'mechanics',
       'howToEarnGolden', 'race', 'playRequirements', 'howToEarn',
       'targetingArrowText', 'durability', 'entourage', 'faction', 'overloa
d',
       'spellDamage', 'hideStats', 'classes', 'multiClassGroup',
       'collectionText'],
      dtype='object')
```

In [97]:
```
# reading the shape, 3116 cards in total
card_data.shape
```

Out[97]:
```
(3116, 32)
```

In [98]:
```
# obtaining a list of all card IDs in the reference card data
card_ids = card_data['dbfId'].astype(str).tolist()
```

In [99]:
```
def contains(cardlist, card):
    '''
    A functiont to check how many times a card ID ("dbfId")
    appear in the cardlist under "card" column.
    '''
    cardcount = Counter(cardlist.split())[card]
    return cardcount
```

In [100]:
```
# for every card in the cardlist, check if it is present in the card column.
# Then add the count (0,1 or 2) onder the respective card's column

for i in (card_ids):
    rated_decks.loc[:,i] = rated_decks.loc[:,'card'].apply(lambda x: contains(
x,i))
```

In [101]:
```
# remove any card column that does not have a card present in the decks at al
l.
# That is, the value of the column is 0 for every row.

rated_decks = rated_decks.loc[:, (rated_decks != 0).any(axis=0)]
rated_decks.head()
```

Out[101]:

	craft_cost	date	deck_archetype	deck_class	deck_format	deck_id	deck_set	deck_type
137	8120	2016-02-19	Miracle Rogue	Rogue	S	432773	Explorers	Ranked Deck
1690	8180	2016-04-21	Ramp Druid	Druid	S	478188	Explorers	Ranked Deck
2414	1680	2016-04-30	Unknown	Warrior	S	520990	Old Gods	Ranked Deck
3527	1860	2016-04-30	Midrange Hunter	Hunter	S	520585	Old Gods	Ranked Deck
3992	8260	2016-06-27	Yogg Druid	Druid	S	579170	Old Gods	Ranked Deck

5 rows × 794 columns

In [102]:
```
# saving processed data
rated_decks.to_csv('processed_HS_data.csv')
```

Checking if all the cards in a deck add up.

In [103]:
```
rated_decks.loc[:, 'cardsaddup'] = rated_decks.iloc[:,12:].sum(axis=1) == 30
rated_decks['cardsaddup'].sum() == len(rated_decks)
```

Out[103]: True

Applying KMeans clustering on both decks and cards

The most straightforward method of clusterning appears to be KMeans clustering. Here, for clustering of decks, the number of clusters used is 20 which is an approximate. For clustering of cards, the n value used is 30. Fine tuning of the n value will be done in a later section.

In [104]:
```
from sklearn.cluster import KMeans
```

Clustering the decks together

Here, KMeans clustering is used to cluster the decks together based on their card choices. The expected results would be group of similar decks and the corresponding cards they have in common.

In [105]:
```
# the array clusters_decks now contains the number of the cluster the deck bel
ongs to
clusters_decks = KMeans(n_clusters=20, random_state=7).fit_predict(rated_decks
.iloc[:,12:])
print(clusters_decks)
```

```
[ 1  4 14 ... 13  1  3]
```

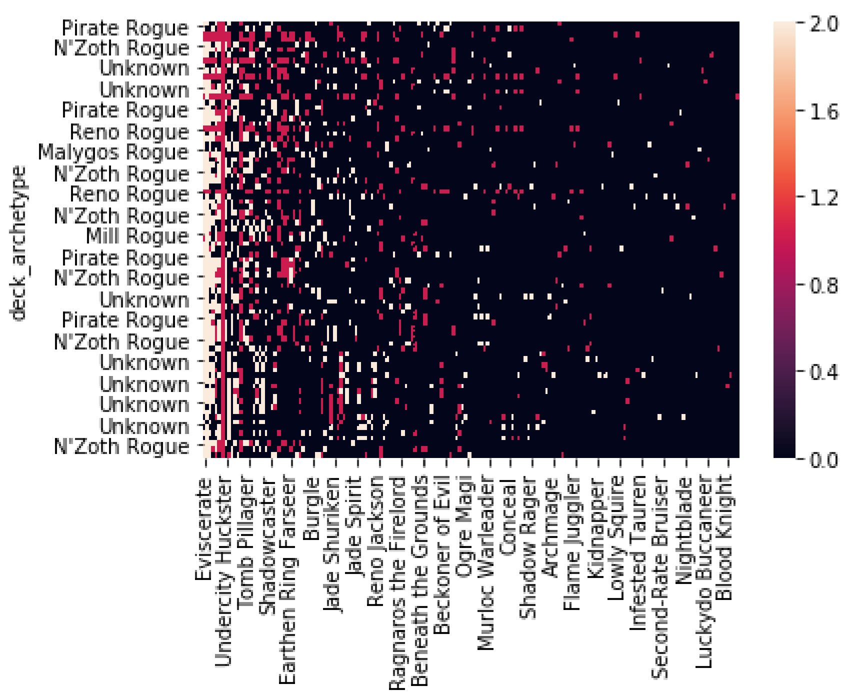
Visualizing the data

Heatmap appears to be the most straightforward way to visualize the data. The decks are on the y-axis. To improve the interpretability, the deck IDs are replaced by the deck archetypes. Deck archetypes are used instead of the deck names since they are more intuitive when it comes to describing type of a deck.
x-axis are the card names. The heatmap will be sorted in order of cards frequency. That is, the card that appears the most among the decks within the cluster will be on the leftmost of the axis.

In [106]:
```
# this lookup table will be used to translate card IDs to names
# the keys are integer. They have to be changed to string
card_lookup = card_data.set_index('dbfId')['name']
card_lookup = {str(k):v for k,v in card_lookup.items()}
```

In [107]:
```
# plotting the heat map of cluster number 1
cluster_number = 3
cluster_1 = rated_decks[clusters_decks == cluster_number].iloc[:,12:].astype(f
loat)

# rename the rows (index)
cluster_1.set_index([rated_decks[clusters_decks == cluster_number].iloc[:,2]],
inplace=True)

# rename the columns
cluster_1.rename(columns=dict(card_lookup), inplace=True)

# drop all clumns with no card present in the decks in the cluster
cluster_1 = cluster_1.loc[:, (cluster_1 != 0).any(axis=0)]

# sort the columns by their sum
cluster_1 = cluster_1.reindex(cluster_1.sum().sort_values(ascending=False).ind
ex, axis=1)

sns.heatmap(cluster_1)
```

Out[107]: <matplotlib.axes._subplots.AxesSubplot at 0x7f25524f3048>



Discussion

Here, we can see the all the Rogue decks are clustered together. Moreover, the main variant appears to be a N'Zoth Rogue. Two copies of strong Rogue cards, preferably with deathrattle, such as Eviscerate, Undercity Huckster, and Tomb Pillager are included in almost all the decks in this cluster.
This demonstrates that the approach works. However, clustering the decks is not as useful as clustering the cards together. As such, clustering the cards will be the next and main appraoch of this project.

Clustering the *cards* together

Similar to clustering the decks done above, this section explores clustering of the cards using the decks as features. Through this, we can explore what cards frequently appear together and hence the cards that apear together can be considered a **package**.

Reformatting the data

From rows of decks with cards as features to rows of cards with the decks they are found in as the features

In [108]:
```
# transpose the table

rated_decks_tpsd = rated_decks.drop(['cardsaddup'], axis=1)
rated_decks_tpsd = rated_decks_tpsd.iloc[:,12:]
rated_decks_tpsd = rated_decks_tpsd.T
print(rated_decks_tpsd.shape)

# creading a deck archetype lookup dictionary
deck_lookup = rated_decks['deck_archetype']
```

```
(782, 1296)
```

In [109]:
```python
# changing the dbfId type form integer to string
card_data['dbfId'] = card_data['dbfId'].astype(int).astype(str)

# joining the card name on dbfId
rated_decks_tpsd = pd.merge(rated_decks_tpsd, card_data[['dbfId','name']], how
='left', left_index=True, right_on='dbfId')

# set the index to be the card name
rated_decks_tpsd.set_index('name', inplace=True)

# drop dfbId column
rated_decks_tpsd.drop(['dbfId'], axis=1, inplace=True)

rated_decks_tpsd.head()
```

Out[109]:

	137	1690	2414	3527	3992	4592	4965	5269	5327	5358	...	325935	325937	3
name														
Oasis Snapjaw	0	0	0	0	0	0	0	0	0	0	...	0	0	
Shadow Word: Death	0	0	0	0	0	0	0	0	0	0	...	0	0	
Silent Knight	0	0	0	0	0	0	0	0	0	0	...	0	0	
Unlicensed Apothecary	0	0	0	0	0	0	0	0	0	0	...	0	0	
Shadow Madness	0	0	0	0	0	0	0	0	0	0	...	0	0	

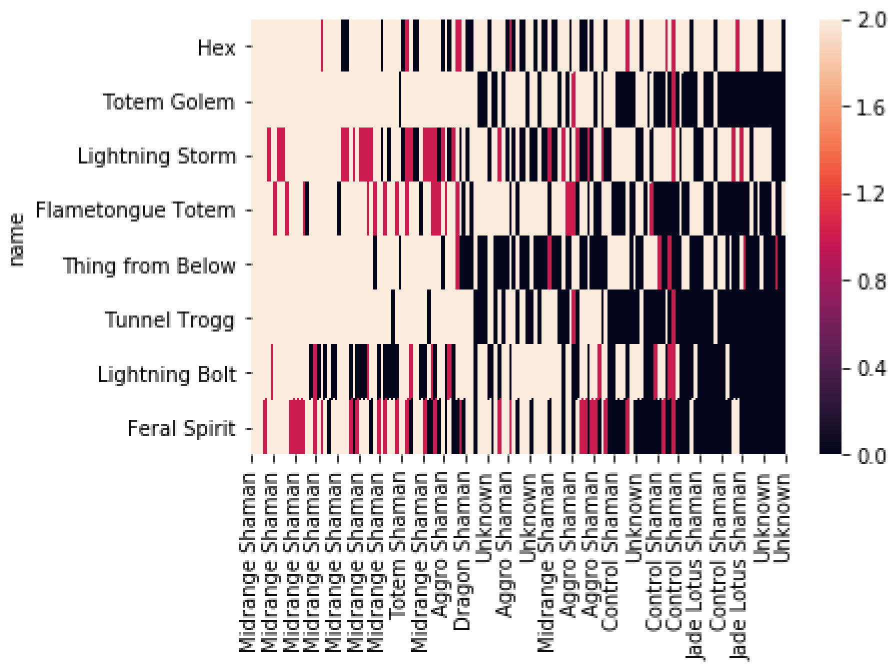
5 rows × 1296 columns

kmeans clustering

In [110]:
```python
kmeansclf = KMeans(n_clusters=30, random_state=7)
clusters_cards = kmeansclf.fit_predict(rated_decks_tpsd)
```

In [111]:
```python
def hs_heatmap(data,clusters,clusternumber):
    '''
    A function that produces a heatmap given the dataset, the KMeans model, an
d the predicted clusters.
    '''
    # subsetting the desired cluster
    card_cluster = data[clusters == clusternumber]#.astype(float)

    # sort the columns by their sum
    card_cluster = card_cluster.reindex(card_cluster.sum().sort_values(ascendi
ng=False).index, axis=1)
    card_cluster.rename(columns=dict(deck_lookup), inplace=True)

    # drop all clumns with no deck present in the decks in the cluster
    card_cluster = card_cluster.loc[:, (card_cluster != 0).any(axis=0)]

    # sort all rows by their sum
    sorted_index = card_cluster.sum(axis=1).sort_values(ascending=False)
    card_cluster = card_cluster.loc[sorted_index.index]

    sns.heatmap(card_cluster)
```

In [112]:
```python
hs_heatmap(rated_decks_tpsd, clusters_cards, 3)
```



Discussion

The heatmap above shows that KMeans clustering is effective at grouping the cards that frequently appear in the same deck togehter. In the example above, the heatmap shows a **package** of Shaman cards. These are the cards that appear together mostly in Midrange Shaman decks. They are Hex, Totem Golem, Lightning Storm, Flametongue Totem, Thing from Below, Tunnel Trogg, Lightining Bolt and Feral Spirit. These cards synergize well together using the Totem tribe and overload effects.

Fine-tuning the model

To find the optimal n value, root mean squared distance is used to measure the tightness of a cluster. This root mean squared value is then used to measure how well the cards are clustered together.

In [113]:
```
def rmsqdist(data,classifier,classifier_output):
    '''
    Calculating the root mean square distance for each cluster
    '''
    clusters = []
    intra_msqdist = []
    num_cards = []
    nclusters = classifier.get_params()['n_clusters']
    for n in range(0, nclusters):
        clsutercentroid = classifier.cluster_centers_[n]
        cards_in_cluster_n = data[classifier_output == n].copy()
        card_num = len(cards_in_cluster_n)

        # use the norm function to obtain the root squared distance
        cards_in_cluster_n.loc[:, 'dist-from-centroid'] = cards_in_cluster_n.a
pply(
            lambda x: np.linalg.norm(x - clsutercentroid), axis=1)
        # finding the mean value
        average_dist = np.mean(cards_in_cluster_n['dist-from-centroid'])
        clusters.append(n)
        intra_msqdist.append(average_dist)
        num_cards.append(card_num)
    return clusters, intra_msqdist, num_cards
```

Beyond root mean suqared

As the number of clusters increase, the root mean squared distance decreases. Given the context of this project, **a package** refers to at least 2 cards working together. As such, even if the mean squared distance is low, a singleton cluster is not desirable. Therefore, the optimal model for this situation would be one where the root mean squared distance is low yet there is minimal number of singletons clusters.
Hence, we look for an "elbow" in the plot of the number of singletons against the number of KMeans cluster. That n value is then used as the optimal number of clusters.
In addition, the inertia value will also be taken into consideration below.

In [114]:

```
# looping through different number of cluster for KMeans, saving the key param
eters each time.
k_vals = []
k_inertia = []
mean_dist = []
singletons = []
for k in range(10,60):
    kmeansclf = KMeans(n_clusters=k, n_init=30, random_state=7)
    clusters_cards = kmeansclf.fit_predict(rated_decks_tpsd)
    clusters, avgdist, num_cards = rmsqdist(rated_decks_tpsd, kmeansclf, clust
ers_cards)
    summary = pd.DataFrame({'clusters' : clusters, 'avgdist' : avgdist, 'num_c
ards' : num_cards}).set_index('clusters')
    mean_dist_for_k = np.mean(summary[summary['num_cards'] >= 2]['avgdist'])
    singleton = len(summary[summary['num_cards'] == 1])
    k_vals.append(k)
    k_inertia.append(kmeansclf.inertia_)
    mean_dist.append(mean_dist_for_k)
    singletons.append(singleton)
    k_vals, mean_dist, singletons
```

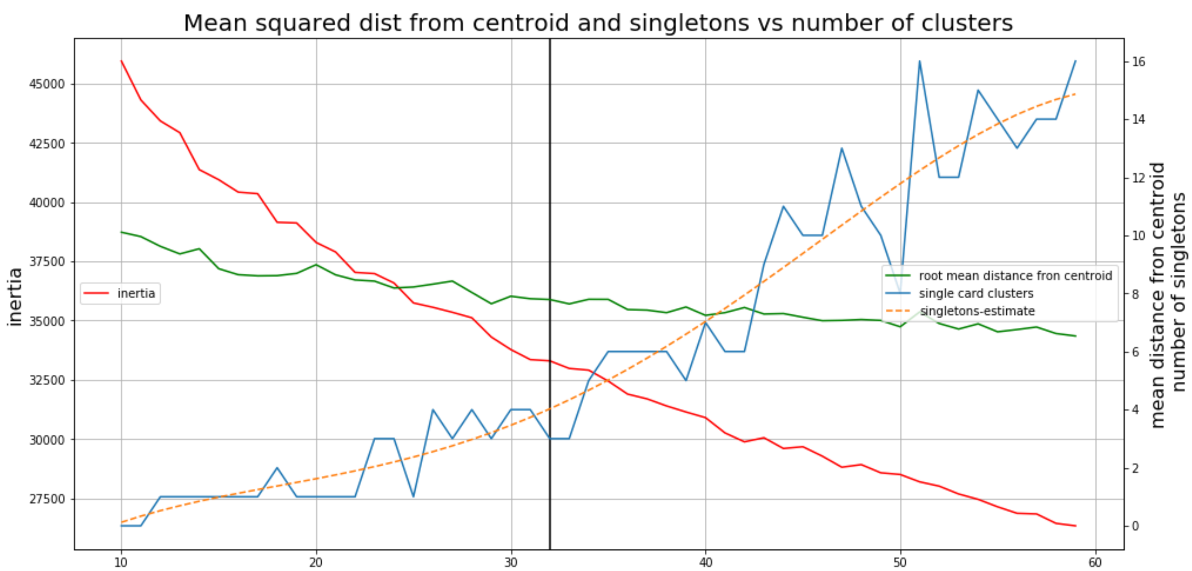
In [115]:

```
# fitting a smooth curve for the number of singletons.

singletons_fit = []
p = np.poly1d(np.polyfit(k_vals,singletons,5))
for i in k_vals:
    singletons_fit.append(p(i))
```

Visualizing the Elbow

Plotting all the parameters above against the number of clusters

In [133]:
```
fig, ax1 = plt.subplots(figsize=(16, 8))
ax2 = ax1.twinx()

ax1.plot(k_vals, k_inertia, label='inertia', c='red')
ax1.set_ylabel("inertia", fontsize=16)
ax2.plot(k_vals, mean_dist, label='root mean distance fron centroid', c='g')
ax2.set_ylabel("mean distance fron centroid\n number of singletons", fontsize=
16)
ax2.plot(k_vals, singletons, label='single card clusters')
ax2.plot(k_vals, singletons_fit, linestyle='--', label='singletons-estimate')
ax1.legend(loc='center left')
ax2.legend(loc='right')
ax1.axvline(x=32, c='black')
ax1.grid()
ax1.set_title("Mean squared dist from centroid and singletons vs number of clu
sters", fontsize=20);
```



The optimal model

From above, the best value of n seems to be approximately **32**. No strong elbow effect is observed and hence the value of 32 is derived from the number of clusters where the number of singletons start to rise sharply. Running the KMeans clustering one more time with n=32. Also, since **packages** are a handful of cards that are used together. The final result of this clustering exercise will be a list of **packages** with cards between 2 to 15 cards (half a deck).

In [134]:
```
kmeansclf = KMeans(n_clusters=32, n_init=50, random_state=7)
clusters_cards = kmeansclf.fit_predict(rated_decks_tpsd)
```

In [135]:
```
# obtaining the clusters with cards between 2 and 15
unique, counts = np.unique(clusters_cards, return_counts=True)
is_package = pd.Series(dict(zip(unique, counts)))
is_package = is_package[is_package <= 15]
is_package = is_package[is_package > 1]
is_package = np.array(is_package.index)
print(is_package)
```

```
[ 0  2  3  4  5  6  7  8 10 11 12 13 15 16 17 18 19 21 23 24 25 26 28 29
 30 31]
```

The above clusters are the clusters which can be defined to be a **package**.
Then, the card names are sorted according to the frequency of appearance within a cluster and tabulated below.

In [136]:

```
package_dict = {}
for i in is_package:
    cards_in_i = rated_decks_tpsd[clusters_cards == i]
    sorted_index = cards_in_i.sum(axis=1).sort_values(ascending=False)
    card_names = np.array(sorted_index.index)
    package_dict[i] = list(card_names)

package_df = pd.DataFrame.from_dict(package_dict,orient = 'index')
package_df.columns = ['card_1', 'card_2', 'card_3', 'card_4', 'card_5',
                      'card_6', 'card_7', 'card_8', 'card_9', 'card_10',
                      'card_11', 'card_12', 'card_13', 'card_14']
package_df.index.name = 'package'
package_df
```

Out[136]:

package	card_1	card_2	card_3	card_4	card_5	card_6	
0	Jade Spirit	Aya Blackpaw	Jade Idol	Jade Blossom	Jade Behemoth	None	
2	Innervate	Swipe	Wrath	Living Roots	None	None	
3	Animal Companion	Kill Command	Eaglehorn Bow	Quick Shot	Savannah Highmane	Unleash the Hounds	Explo
4	Fireball	Frostbolt	Arcane Intellect	Mana Wyrm	Arcane Missiles	Sorcerer's Apprentice	Arc
5	Power Word: Shield	Shadow Word: Death	Shadow Word: Pain	Northshire Cleric	Holy Nova	None	
6	Hex	Lightning Storm	Thing from Below	Mana Tide Totem	None	None	
7	Eviscerate	Backstab	SI:7 Agent	Fan of Knives	Sap	Gadgetzan Auctioneer	Pr
8	Totem Golem	Flametongue Totem	Tunnel Trogg	Lightning Bolt	Feral Spirit	Rockbiter Weapon	Flame
10	Sylvanas Windrunner	Entomb	Excavated Evil	Circle of Healing	Auchenai Soulpriest	Thoughtsteal	Caba
11	Acolyte of Pain	Fiery War Axe	Execute	Ravaging Ghoul	Slam	None	
12	Lava Shock	Elemental Destruction	Healing Wave	Ancestral Knowledge	Stormcrack	None	
13	Kor'kron Elite	Frothing Berserker	Blood To Ichor	None	None	None	
15	Bluegill Warrior	Tirion Fordring	Murloc Warleader	Forbidden Healing	Ivory Knight	Ragnaros, Lightlord	So
16	Bloodmage Thalnos	Flamestrike	Water Elemental	Forgotten Torch	Ice Block	Polymorph	Al
17	Shield Block	Shield Slam	Brawl	Bloodhoof Brave	Justicar Trueheart	Bash	
18	Wild Growth	Raven Idol	Nourish	Feral Rage	Mire Keeper	Fandral Staghelm	
19	Wild Pyromancer	Truesilver Champion	Consecration	Aldor Peacekeeper	Equality	None	
21	Maelstrom Portal	Spirit Claws	None	None	None	None	
23	Houndmaster	Fiery Bat	Call of the Wild	Infested Wolf	Kindly Grandmother	Huge Toad	Kir
24	Soulfire	Doomguard	Silverware Golem	Malchezaar's Imp	Darkshire Librarian	None	
25	Druid of the Claw	Power of the Wild	Violet Teacher	Savage Roar	Mark of Y'Shaarj	Druid of the Saber	Stra
26	Twilight Guardian	Blackwing Corruptor	Faerie Dragon	Blackwing Technician	Netherspite Historian	Book Wyrm	Twilig
28	Southsea Deckhand	N'Zoth's First Mate	Arcanite Reaper	Bloodsail Raider	Upgrade!	Dread Corsair	Hei

package	card_1	card_2	card_3	card_4	card_5	card_6	
29	Defender of Argus	Abusive Sergeant	Dark Peddler	Knife Juggler	Imp Gang Boss	Power Overwhelming	V
30	C'Thun's Chosen	Disciple of C'Thun	Beckoner of Evil	C'Thun	Twilight Elder	Twin Emperor Vek'lor	
31	Argent Squire	Argent Horserider	Keeper of Uldaman	Bilefin Tidehunter	Blessing of Kings	Divine Favor	Self

Notable clusters

In [137]:
```
package_df[package_df.index.isin([3,16,28])]
```

Out[137]:

package	card_1	card_2	card_3	card_4	card_5	card_6	card_7	card_8
3	Animal Companion	Kill Command	Eaglehorn Bow	Quick Shot	Savannah Highmane	Unleash the Hounds	Explosive Trap	Freezing Trap
16	Bloodmage Thalnos	Flamestrike	Water Elemental	Forgotten Torch	Ice Block	Polymorph	Alexstrasza	Mirror Image
28	Southsea Deckhand	N'Zoth's First Mate	Arcanite Reaper	Bloodsail Raider	Upgrade!	Dread Corsair	Heroic Strike	Mortal Strike

Conclusion

Looking at the table above, the packages identified by the KMeans clustering can be quite accurate. We can see popular packages such as **Hunter core cards** (cluster number 3), **Freeze Mage** (cluster number 16) or **Pirate Warrior** (cluster number 28).
However, KMeans clustering does not allow for the same card to appear in different clusters. This, happends often in Hearthstone. As such, more sophisticated tools will have to be explored for further improve the accuracy of this **package** identificaiton exercise.

In [ ]:
```

```