Clothing Size Recommendation and Fit Prediction for RentTheRunWay Applying Text and Non-text Model

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1 Key Words

Recommender System, Latent Factors, Linear Regression, Logistic Regression, Text, Bags-of-words

2 Summary

Online shopping have become more and more popular in recent decades, and online clothes shopping is one of the most popular aspects. A critical challenge for online customers is to find the right size of clothes without actually trying on them. Clothing size recommendation and fit prediction are critical for improving customers' shopping experience and reduce product returning rates. In this paper, we perform a customer size analysis and generate a fitting predictor from customer feedback and product information using logistic regression, linear regression and bags-of-words analysis.

3 Dataset Analysis

In this case, we used the dataset from the RentTheRunway website, which is a unique platform that allows women to rent clothes for various occasions. This dataset contains customer feedback such as ratings, reviews and fit feedback (small/fit/large etc.) and also information about customer and product such as user/item measurements and clothes category information.

3.1 Dataset Characters

We have 192,544 rows of data, that is, 192,544 records of transactions in total. The total number of customers is 105,508 and the number of products is 5,850. Each record has several features, including customer ID, body figure information, review, and fit feedback and product category and size. The detail information about each row of record is given in the table below. Among all these features, the most valuable one should be the 'fit' feature, which contains three attributes: 'small', 'fit' and 'large'. It intuitively demonstrate the user's feedback on whether the clothes fit or not. And also the customer's weight, height, and bust size also directly determine the size of the fit-able product.

FEATURE DESCRIPTION:	
item_id	unique product id
weight	weight measurement of customer
rented for	purpose clothing was rented for
body type	body type of customer
review_text:	review given by the customer
review_summary:	summary of the review
size	the standardized size of the product
rating	rating for the product
age	age of the customer
category	the category of the product
bust size	bust measurement of customer
height	height of the customer
fit	fit feedback
user_id	a unique id for the customer

3.2 Exploratory Dataset Analysis

By looking at the head of the data, we found some intuitive information about the data:

1. There are a lot of missing values across the

dataframe, which need to be handled.

2. Cup-size contains multiple preferences - which will need handling if we wish to define cup sizes as 'category' datatype.

3. Height column needs to be parsed for height in a numerical quantity, it is a string right now.

4. Weight values contain the unit 'lb', which need to be erased to get only the numerical data.

5. Some columns have spaces which could interfere the classification process.

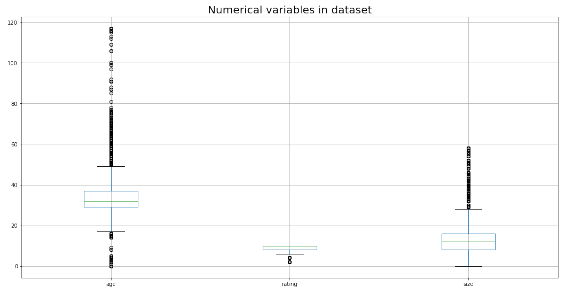
Then in order to see how many values in each column and in what percentage does they miss, we construct a table about the missing feature statistics.

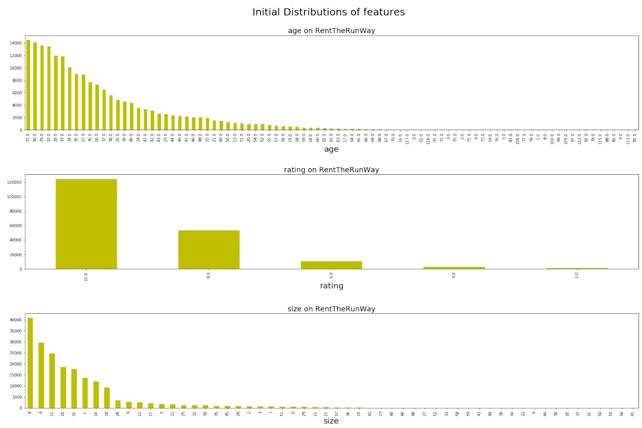
MISSING FEATURE		
Feature	**total_missing**	**perc_missing**
fit	0	0
user_id	0	0
bust_size	18411	9.56197
item_id	0	0
weight	29982	15.571506
rating	82	0.042588
rented for	10	0.005194
review_text	0	0
body_type	14637	7.601899
review_summary	0	0
category	0	0
height	677	0.351608
size	0	0
age	960	0.498587
review_date	0	0

We did some more statistical analysis of the data here for a closer look. According to the statistical description, we could found that most size are around 2-16, but the maximum size is 58, which certainly must be something other than US sizing (It is actually an Italian sizing).

STATISTICAL DESCRIPTION					
Feature	**Age**	**Item_id**	**Rating**	**Size**	**User_id**
count	191584	1.93e05	192462	192544	192544
mean	33.8710	1.05e06	9.0923	12.245	499494
std	8.0580	8.05e05	1.4300	8.494	289059
min	0	1.23e05	2	0	9
25%	29	1.95e05	8	8	250654
50%	32	9.48e05	10	12	499419
75%	37	1.68e06	10	16	750974
max	117	2.97e06	10	58	999997

And here is a boxplot and distribution chart of numerical variables for a better sense of the outliers. We can see that the rating data is very clean and however we should handle the size data carefully.

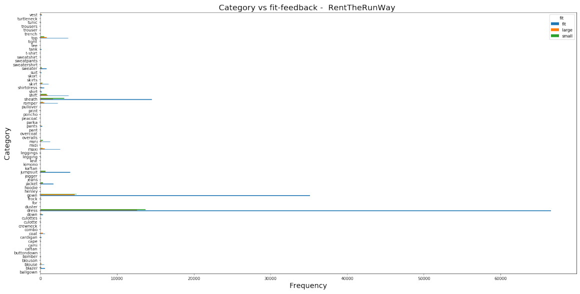




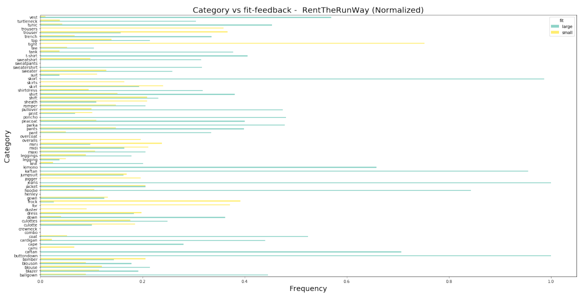
Then we want to visualize how the items of different categories distributed in terms of fit, length and quality. We decided to employ two distributions in categories here due to the highly imbalance of each category:

1. Non-normalized - viewing the frequency counts directly - for comparison across categories. We also include the best fit and quality measure in this plot.

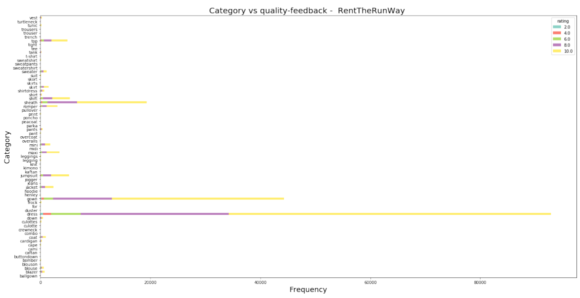
2. Normalized - viewing the distribution for the category after normalizing the counts, amongst the category itself - it would help to compare what are major reasons for return amongst the category itself. We exclude the best sizing and quality measures, so as to focus on the pre-dominant reasons of return per category.



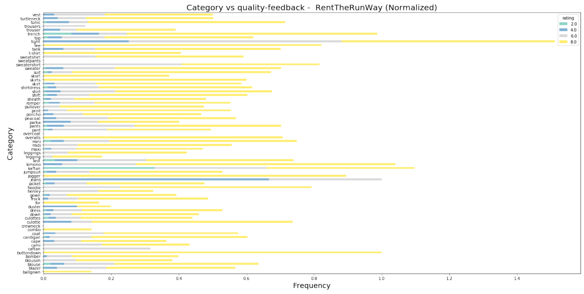
We observe that best-fit response (fit) has been highest for dresses, gown and sheath categories. Overall maximum bad fit-feedback has belonged mostly to 2 categories- dress, gown, and sheath categories follow. Cami, culottes, and blouson are not prominent in our visualization- mostly due to the lack of transactions in these categories.



Here, we can see that amongst the categories themselves, skirt, jeans, and button-down categories usually have more returns due to large sizing. Top, gown, and trousers usually have frequent returns due to small sized buys.



Most people have rated the categories of dress 10, and gown, sheath categories have similar ratings of 10. All the trends in terms of share of ratings seems to be constant across categories.



Here also we can assert our previous observation that all the categories share similar share of ratings. To jeans, tight, and trench seem to have a higher share than normal of bad ratings (2.0 or 4.0) in terms of quality.

4 Predictive Task

4.1 Non-Text Task

Based on the analysis of the database, it's very intuitive that we could use the non-text data of a customer's body figure information and feedback to estimate the customer's body size, and compare it with the product size the user just bought and predict whether the product the user bought would fit. We could use the user's height, weight and bust size to estimate user's body size, therefor we could use a linear regression model. We would use the first 80% data for training the predictor, 10% for validation and the rest 10% for testing. And after that we could compare it with the product size the user bough and if the size are similar, it would be a fit feedback, or other would be a large or small feedback. We would use a classification method here, we would use logistic regression model here since each feature are certainly dependent. And we would calculate the MSE to evaluate the model's performance.

4.2 Text Task

We also found that the user's review of the product may contain important information. Since whether clothes fit or not is not only due to the users' size choice, but also relies on the actual size of the clothes. There is a possibility that the size distribution of the product is not the standard clothing size. We would use a Support Vector Machine (SVM) regression with one-vs-the-rest scheme for multiple results, and give the possibility of each fitting result, and pick the largest one as final fitting result, and evaluate the model with the prediction precision.

5 Model

In order to predict whether a user will fit a specific product and predict users' feedback about whether one product is fit for them using review, we designed a model based on non-text information like users' body size and products' size and category and a different model based on users' review text and summary, which are text information.

5.1 Non-Text Model

The basic idea of non-text model is very intuitive. We have information about users' basic body size, such like height, weight and bust size. We also have the size of products they purchased and the feedback of fit or not. Therefore, we can use the users purchase history which they think that is fit for them to predict the size of fitted product. We designed the X feature as following. $X[0]$ is bias term, $X[1]$ is height, $X[2]$ is weight, $X[3]$ is bust base size, and the remaining are the one hot of bust cup. y is the size of fitted product user purchased.

$$X = [1, 165.1, 120, 34.0, 0, ..., 1, 0, 0], y = [32]$$

We use Euclidean 2-norm as the cost function and try to minimizes it. However, there is an issue. The products have different categories, so the real size of users should be different for different categories. For example, a user may fit dress with size 30, but fit T-short with size 28. And the regressor also should be different categories because whether a product is fitted for user is determined by different part of body's size, such as the bust size would not influence size of pants. Therefore, we train multiple regressors for each category. The distribution of category with fit data is present as last section. We can find that the distribution of this dataset among different categories is extremely unbalanced, large amounts of data concentrated under certain categories, like dress and gown.

5.2 Text Model

In this dataset, each purchase history contains review text and review summary. These information can help us to predict feedback of user if they write the review but not determine whether it is fitted in the future. After we observed the review of users, we found that if user were not satisfied with the size of product, they would comment some word like "too tight" or "to loose". When the size is fitted for them, the words of reviews are typically positive, such like "Perfect" and "like". So we can use these interesting properties to make prediction using review text and summary. We counted the frequency of each word and choose the top 1000 words to build feature X, so the X's dimension is $(1000, 1)$, and the dimension of output should be $(3, 1)$, each row means the probability of "fit", "small", or "large". In order to classify multiple labels, we used linear support vector classification with one-vs-the-rest scheme, which means the model will classify "fit" as one class and "small" and "large" as one class, same as "small" and "large". Finally, we choose the label with maximum probability as the prediction. For example, if the output is following, we will choose first label ("fit") as output, because 0.9 is larger than 0.3 ("small") and 0.2 ("large").

$$y = [0.9, 0.3, 0.2]$$

6 Literature

We adopt the dataset collected by Rishabh Misra, Mengting Wan and Julian McAuley from the RentTheRunway website in 2018. Following type of information is available in the datasets: ratings and reviews, fit feedback (small/fit/large), customer/product measurements, category information. This dataset is highly sparse, with most products and customers having only a single transaction. Specially, a 'product' here refers to a specific size of a product, as the data is used to predict fitness for associated catalog sizes. Also, since different clothing products use different sizing conventions, sizes are standardized into a single numerical scale preserving the order.

There are also some similar datasets used in the past to perform fit prediction, such as ModCloth collected by Rishabh Misra and Julian McAuley in 2018, Amazon shoes datasets collected by Vivek Sembium in 2017.

Because ModCloth has relatively more cold products and costomers (products and customers with very few transactions) compared to RentTheRunWay, and RentTheRunWay has richer contents in text comments and more diverse categories of the products than Amazon shoes datasets, we decided to build our recommender systems based on it at last.

As we know, retailers often allow customers to provide fit feedback (small, fit, large) during the product return process or when leaving reviews, predictive models have been recently developed based on this kind of data. A few recent approaches to this problem use two sets of latent variables to recover products' and customers' "true" sizes, and model the fit as a function of the difference between the two variables.

Specifically, [2] recovers products' and customers' "true" sizes and uses these as features in a standard classifier for fit prediction. It assumes a single latent variable for each customer and product and uses $f_w(t) = w(u_{t_c} - v_{t_p})$ as the scoring function. The learned features are then used in Logistic Regression (LR) for final classification. And [3] extends the above method and proposes Bayesian logit and probit regression models with ordinal categories to model fit.

However, [1] differs from these studies in that [1] focus on capturing fit semantics and handle label imbalance issues using metric learning approaches with prototyping. It uses the metric learning approach, instead of Logistic Regression, with K Latent Factors to produce the final classification. It assigns a score to each transaction which is indicative of the fitness of a corresponding product on the corresponding customer. In particular, if a customer c buys a product p (e.g. a medium jacket) which is a specific size of the parent product pp (the corresponding jacket), then the fitness score of this transaction t is modeled as

$$f_w(t) = \langle w, \alpha \oplus b_{tc} \oplus b_{tpp} \oplus (u_{tc} \odot v_{tp}) \rangle$$

where u_{tc} and v_{tp} are K-dimensional latent features, α is a global bias term, $\oplus$ denotes concatenation and $\odot$ denotes element-wise product.The bias term b_{tpp} captures the notion that certain products tend to be reported more 'unfit' because of their inherent features/build, while b_{tc} captures the notion that certain customers are highly sensitive to fit while others are more accommodating.

Therefore, inspired by these models, we apply Linear Regression based on the "true" features of the customers, such as height, weight, and bust size to predict the estimated size of the product in specific category. Then we calculate the difference between the predictive size and "true" size of the product, then we employ Logistics Regression to draw the conclusion whether the this product is small or large or fit to the customer.

7 Results

7.1 Non-Text Model Result

We split the data by their category, and use logistic regression to train each data set. Finally, we use mean squared error to evaluate the validation data set of each different categories. Unfortunately, some categories don't have enough samples, such like "hoodie" with 5 samples and 'sweatershirt' with 2 samples. Due to the failure of training those categories, we just output 'fit' as prediction latter. The following table is the MSE of a part of categories. The result is not very good, and data of some categories are facing underfitting problems.

dress	18.209353628943305
mini	9.242105263157894
frock	2.7
cape	6.75
gown	18.094196804037004

After predict the size the user will purchase, we use the prediction to compare with the size they selected. If the difference is large than a threshold (We used 10), we output "small" or "large", otherwise we output "fit". The result is listed as following table.

Accuracy	0.7186283216066671
Precision of fit	0.7333474606201879
Precision of small	0.2808022922636103
Precision of large	0.3007518796992481
recall of fit	0.7333474606201879
recall of small	0.2808022922636103
recall of large	0.3007518796992481

Although the overall accuracy is 70 percent, the performance of this model is actually poor because most of samples of this dataset is "fit". The precision and recall of "small" and "large" is not good. Therefore, we just this this result as baseline, and try to use text model.

7.2 Text Model Result

We first counted the words in the review dataset and then choose the top 1000 word to build feature vector for each data input. After that, train the model using SVM regression with one-vs-the-rest scheme. In order to get the final output, we choose the label with the largest probability as output. The result of this model is listed as following table.

Accuracy	0.8051314012672691
Precision of fit	0.816711915535445
Precision of small	0.7111913357400722
Precision of large	0.7573415765069552
recall of fit	0.816711915535445
recall of small	0.7111913357400722
recall of large	0.7573415765069552

The performance of this model is much better than previous one! Precision and recall of "small" and "large" are greater then 70 percent. It's an exciting result, let's analyze the parameters of this model. In this model, the shape of trainable parameter theta should be $(3, 1000)$, $parameter[i][j]$ means the contribution of j_{th} word to output label i. Therefore, we find the words with large contribution to "fit", "small" and "large" as following table.

Word	Output	Value
true	fit	0.7571825051953963
dream	fit	0.14057191092226481
excellent	fit	0.11646162336380528
small	small	0.37736246807921575
tight	small	0.33330277801703184
sized	small	0.2321831966988043
large	large	0.5419253264148798
big	large	0.4571822393951811
baggy	large	0.36504435364737603

The results are pretty interesting. We can find some positive words like "dream" and "excellent" are contributing to "fit" label. Words likes "small" and "tight" have a big impact to label "small". We also found something more interesting, some comparative words like "smaller" have a great contribution to the label "large", which has a opposite meaning with itself, because when people think the cloth is large, they would probably say that I want a smaller one.

8 Conclusion

In this paper, we used text and non-text regression model to predict the clothing fitness of a user's purchase. After using the methods like logistic regression, linear regression and bags-of-words analysis, we got a ideal and interesting result by text-model with bags-of-words analysis. However, these models are still not good enough for high accuracy results. The problem of recommending sizes to customers is It would be much better to use K-clustering and latent factors.

9 References

1. Rishabh Misra, Mengting Wan, Julian McAuley "Decomposing Fit Semantics for Product Size Recommendation in Metric Spaces". RecSys, 2018.

2. Vivek Sembium, Rajeev Rastogi, Atul Saroop, and Srujana Merugu. 2017. Recommending Product Sizes to Customers. In RecSys.

3. Vivek Sembium, Rajeev Rastogi, Lavanya Tekumalla, and Atul Saroop. 2018. Bayesian Models for Product Size Recommendations. In Proceedings of the 2018 World Wide Web Conference on World Wide Web.

In [33]:
```
import json
import gzip
import numpy as np
import string
import random
import operator
from collections import defaultdict
from sklearn.linear_model import LogisticRegression
# from pylmnn.lmnn import LargeMarginNearestNeighbor as LMNN
#from pylmnn.plots import plot_comparison
from collections import defaultdict
import matplotlib.pyplot as plt
import pandas as pd

def parseData(file):
    for l in open(file,'r'):
        yield json.loads(l)

def remove_punctuation(text):
    return ''.join([c.lower() for c in text if c not in set(string.punct
uation)])

np.random.seed(5)
```

Data Visualization

In [58]:
```
data1 = list(parseData('./renttherunway_final_data.json'))
```

In [59]:
```
data1[0]
```

Out[59]:
```
{'fit': 'fit',
 'user_id': '420272',
 'bust size': '34d',
 'item_id': '2260466',
 'weight': '137lbs',
 'rating': '10',
 'rented for': 'vacation',
 'review_text': "An adorable romper! Belt and zipper were a little hard
to navigate in a full day of wear/bathroom use, but that's to be expect
ed. Wish it had pockets, but other than that-- absolutely perfect! I go
t a million compliments.",
 'body type': 'hourglass',
 'review_summary': 'So many compliments!',
 'category': 'romper',
 'height': '5\' 8"',
 'size': 14,
 'age': '28',
 'review_date': 'April 20, 2016'}
```

In [60]:
```
mc_df = pd.read_json('./renttherunway_final_data.json', lines=True)
mc_df.head()
```

Out[60]:

	fit	user_id	bust size	item_id	weight	rating	rented for	review_text	body type	review_summary
0	fit	420272	34d	2260466	137lbs	10.0	vacation	An adorable romper! Belt and zipper were a lit...	hourglass	So many compliments!
1	fit	273551	34b	153475	132lbs	10.0	other	I rented this dress for a photo shoot. The the...	straight & narrow	I felt so glamourous!!!
2	fit	360448	NaN	1063761	NaN	10.0	party	This hugged in all the right places! It was a ...	NaN	It was a great time to celebrate the (almost) ...
3	fit	909926	34c	126335	135lbs	8.0	formal affair	I rented this for my company's black tie award...	pear	Dress arrived on time and in perfect condition.
4	fit	151944	34b	616682	145lbs	10.0	wedding	I have always been petite in my upper body and...	athletic	Was in love with this dress !!!

In [61]:
```
mc_df.columns
```

Out[61]:
```
Index(['fit', 'user_id', 'bust size', 'item_id', 'weight', 'rating',
       'rented for', 'review_text', 'body type', 'review_summary', 'cat
egory',
       'height', 'size', 'age', 'review_date'],
      dtype='object')
```

In [63]:
```
# mc_df.columns = ['age', 'body_type', 'bust_size', 'category', 'fit',
 'height', 'item_id',
#        'rating', 'rented for', 'review_date', 'review_summary', 'revie
w_text',
#        'size', 'user_id', 'weight']
mc_df.columns = ['fit', 'user_id', 'bust_size', 'item_id', 'weight', 'ra
ting',
       'rented for', 'review_text', 'body_type', 'review_summary', 'cate
gory',
       'height', 'size', 'age', 'review_date']
```

In [64]:
```
mc_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192544 entries, 0 to 192543
Data columns (total 15 columns):
fit               192544 non-null object
user_id           192544 non-null int64
bust_size         174133 non-null object
item_id           192544 non-null int64
weight            162562 non-null object
rating            192462 non-null float64
rented for        192534 non-null object
review_text       192544 non-null object
body_type         177907 non-null object
review_summary    192544 non-null object
category          192544 non-null object
height            191867 non-null object
size              192544 non-null int64
age               191584 non-null float64
review_date       192544 non-null object
dtypes: float64(2), int64(3), object(10)
memory usage: 22.0+ MB
```

In [65]:
```
missing_data = pd.DataFrame({'total_missing': mc_df.isnull().sum(), 'perc_missing': (mc_df.isnull().sum()/192544)*100})
missing_data
```

Out[65]:

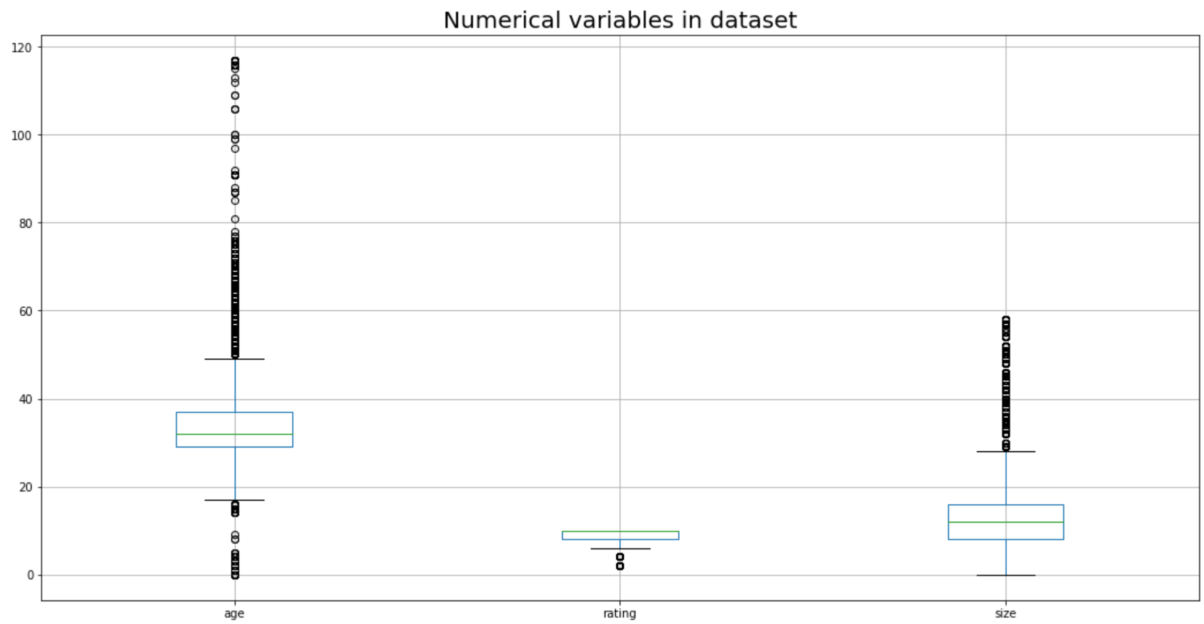
	total_missing	perc_missing
fit	0	0.000000
user_id	0	0.000000
bust_size	18411	9.561970
item_id	0	0.000000
weight	29982	15.571506
rating	82	0.042588
rented for	10	0.005194
review_text	0	0.000000
body_type	14637	7.601899
review_summary	0	0.000000
category	0	0.000000
height	677	0.351608
size	0	0.000000
age	960	0.498587
review_date	0	0.000000

In [9]:
```
mc_df.describe()
```

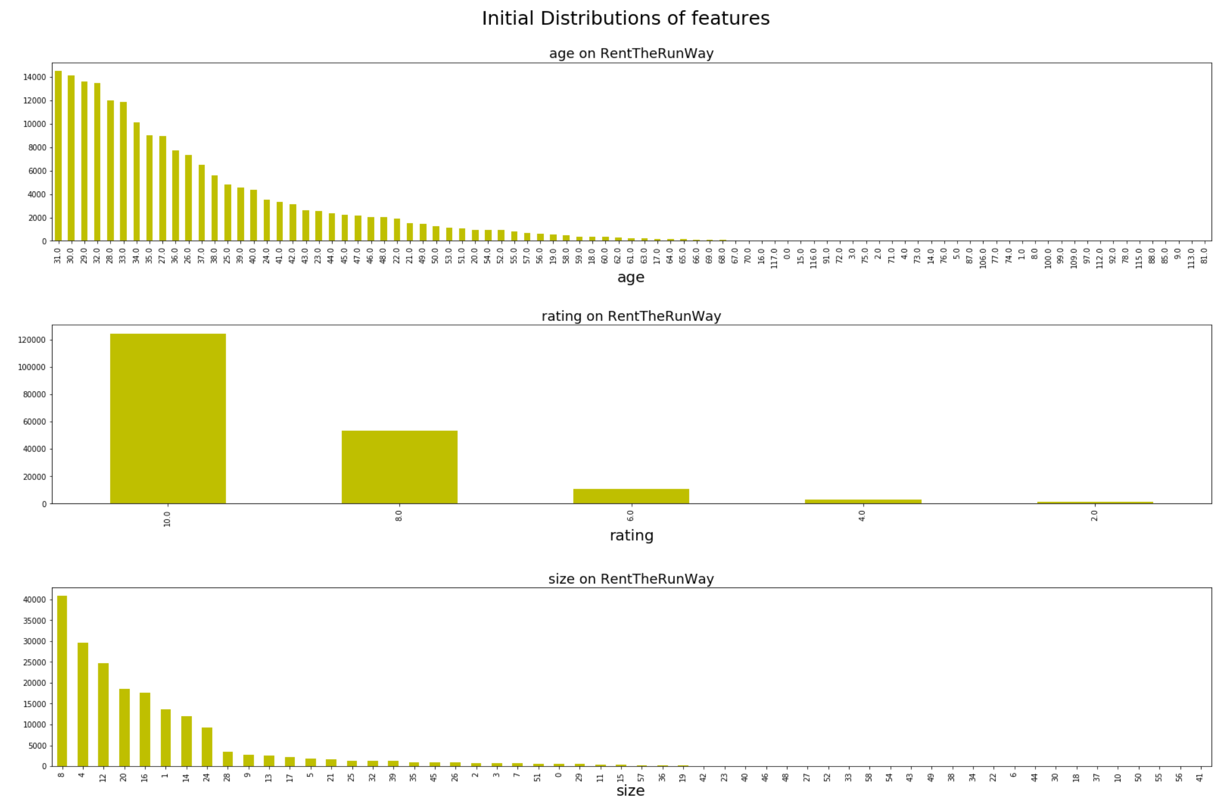
Out[9]:

	age	item_id	rating	size	user_id
count	191584.000000	1.925440e+05	192462.000000	192544.000000	192544.000000
mean	33.871017	1.045684e+06	9.092371	12.245175	499494.100149
std	8.058083	8.053148e+05	1.430044	8.494877	289059.719328
min	0.000000	1.233730e+05	2.000000	0.000000	9.000000
25%	29.000000	1.950760e+05	8.000000	8.000000	250654.250000
50%	32.000000	9.483960e+05	10.000000	12.000000	499419.000000
75%	37.000000	1.678888e+06	10.000000	16.000000	750974.000000
max	117.000000	2.966087e+06	10.000000	58.000000	999997.000000

In [10]:
```
num_cols = ['age','rating','size']
plt.figure(figsize=(18,9))
mc_df[num_cols].boxplot()
plt.title("Numerical variables in dataset", fontsize=20)
plt.show()
```



In [63]:
```
def plot_dist(col, ax):
    mc_df[col][mc_df[col].notnull()].value_counts().plot('bar', facecolo
r='y', ax=ax)
    ax.set_xlabel('{}'.format(col), fontsize=20)
    ax.set_title("{} on RentTheRunWay".format(col), fontsize= 18)
    return ax

f, ax = plt.subplots(3,1, figsize = (22,15))
f.tight_layout(h_pad=9, w_pad=2, rect=[0, 0.03, 1, 0.93])
cols = ['age','rating','size']
k = 0
for i in range(3):
    plot_dist(cols[k], ax[i])
    k += 1
__ = plt.suptitle("Initial Distributions of features", fontsize= 25)
```



In [64]:
```
def plot_barh(df,col, cmap = None, stacked=False, norm = None):
    df.plot(kind='barh', colormap=cmap, stacked=stacked)
    fig = plt.gcf()
    fig.set_size_inches(24,12)
    plt.title("Category vs {}-feedback - RentTheRunWay {}".format(col,
'(Normalized)' if norm else ''), fontsize= 20)
    plt.ylabel('Category', fontsize = 18)
    plot = plt.xlabel('Frequency', fontsize=18)

def norm_counts(t):
    norms = np.linalg.norm(t.fillna(0), axis=1)
    t_norm = t[0:0]
    for row, euc in zip(t.iterrows(), norms):
        t_norm.loc[row[0]] = list(map(lambda x: x/euc, list(row[1])))
    return t_norm
```

In [65]:
```
mc_df.category.value_counts()
```

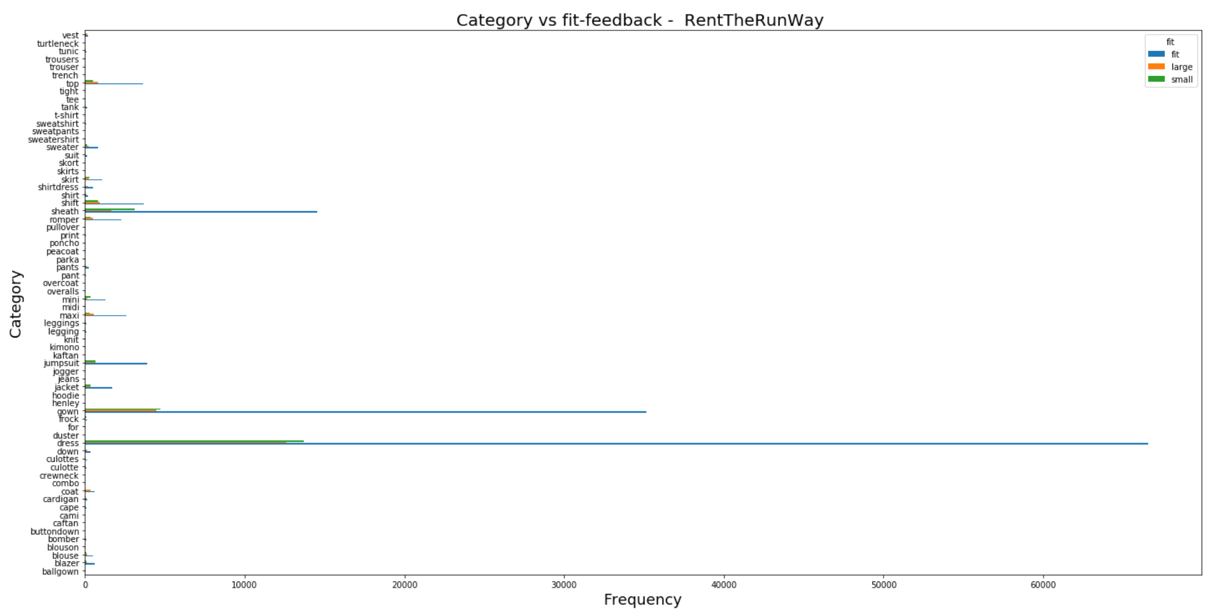
Out[65]:
```
dress            92884
gown             44381
sheath           19316
shift             5365
jumpsuit          5184
top               4931
maxi              3443
romper            3070
jacket            2404
mini              1751
skirt             1531
sweater           1149
coat               980
blazer             782
shirtdress         729
blouse             651
down               464
pants              422
vest               278
shirt              277
cardigan           241
frock              205
culottes           188
tank               181
tunic              162
bomber             128
sweatshirt         125
suit               123
leggings           112
pant               107
                 ...
poncho              48
peacoat             39
turtleneck          34
kimono              30
tee                 22
trench              20
trousers            18
parka               17
kaftan              17
cami                16
ballgown            16
tight               15
hoodie              14
blouson             14
t-shirt             13
duster              12
combo                8
henley               8
skirts               7
skort                7
for                  7
overalls             6
jogger               6
jeans                5
sweatershirt         4
caftan               4
```

```
sweatpants          2
overcoat            2
crewneck            1
buttondown          1
Name: category, Length: 68, dtype: int64
```

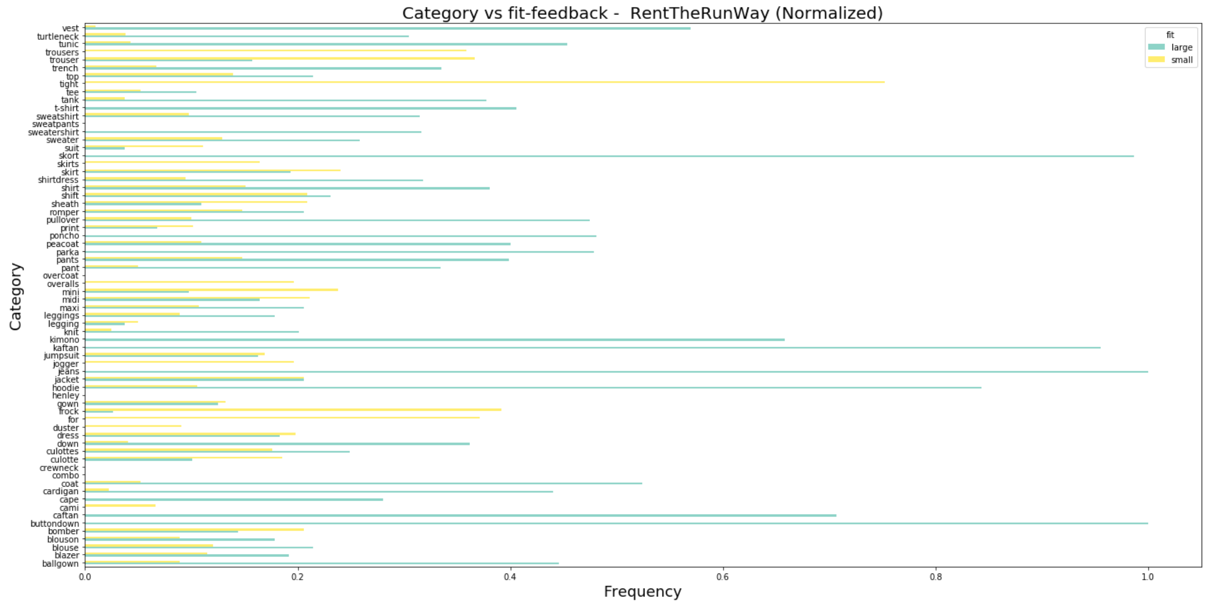
- Remark : # category = 68

In [66]:
```
g_by_category = mc_df.groupby('category')
cat_fit = g_by_category['fit'].value_counts()
cat_fit = cat_fit.unstack()
cat_fit_norm = norm_counts(cat_fit)
cat_fit_norm.drop(['fit'], axis=1, inplace=True)
plot_barh(cat_fit, 'fit')
```

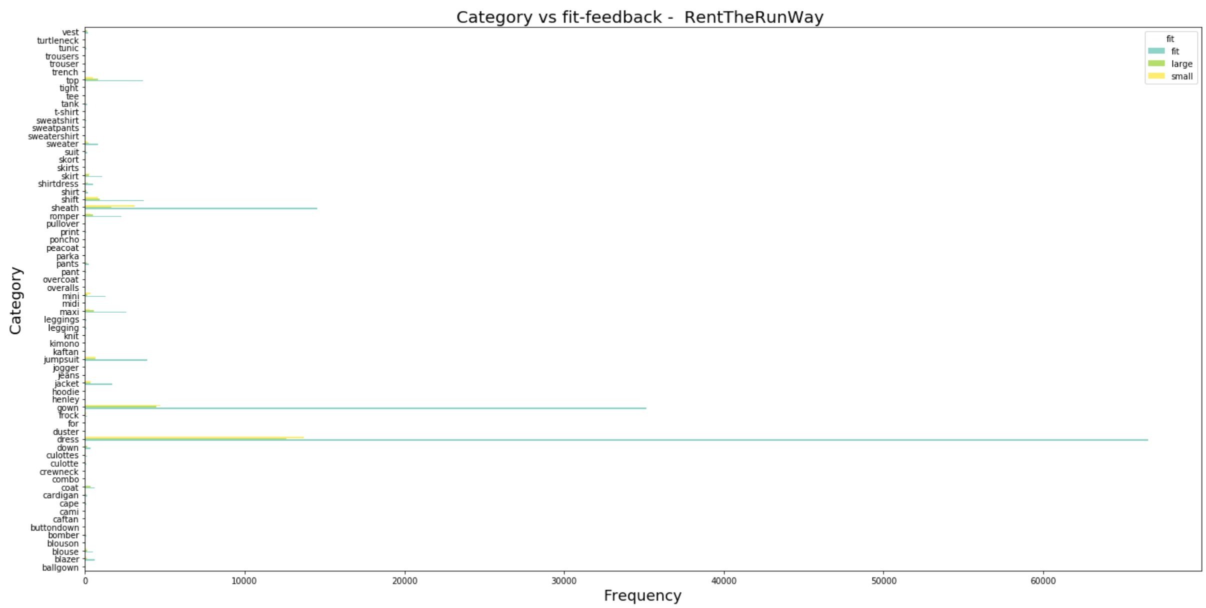
```
/Users/sungen/Documents/Jupyter/anaconda3/lib/python3.7/site-packages/i
pykernel_launcher.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  del sys.path[0]
```



In [67]:
```
plot_barh(cat_fit_norm, 'fit', norm=1, cmap='Set3')
```

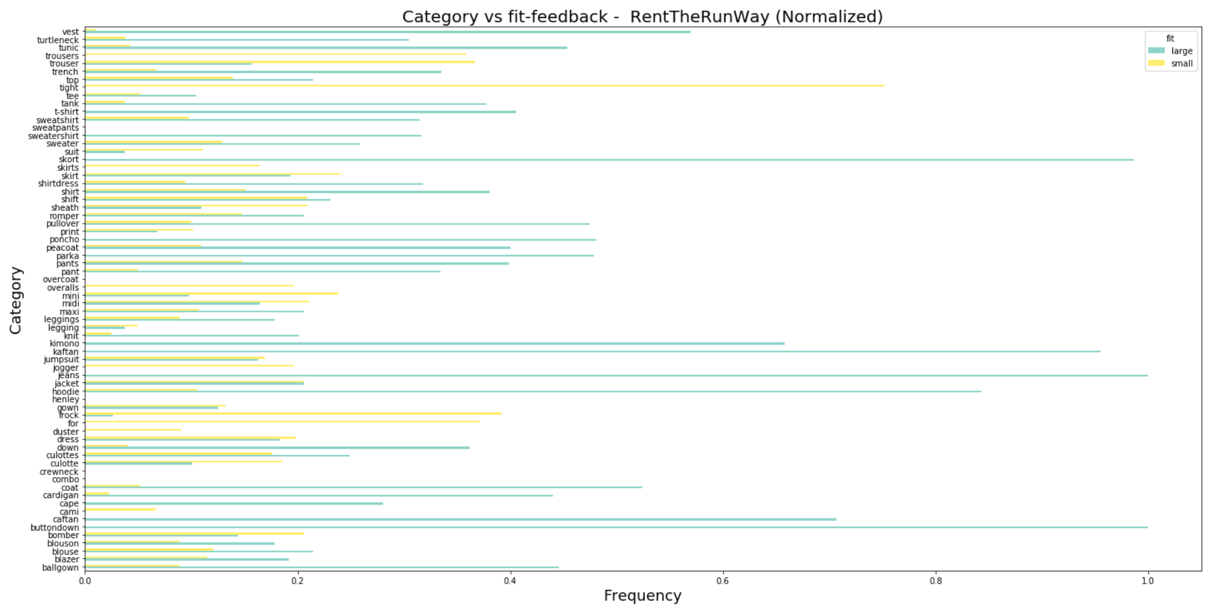


In [70]:
```
cat_len = g_by_category['fit'].value_counts()
cat_len = cat_len.unstack()
plot_barh(cat_len, 'fit', 'Set3')
```

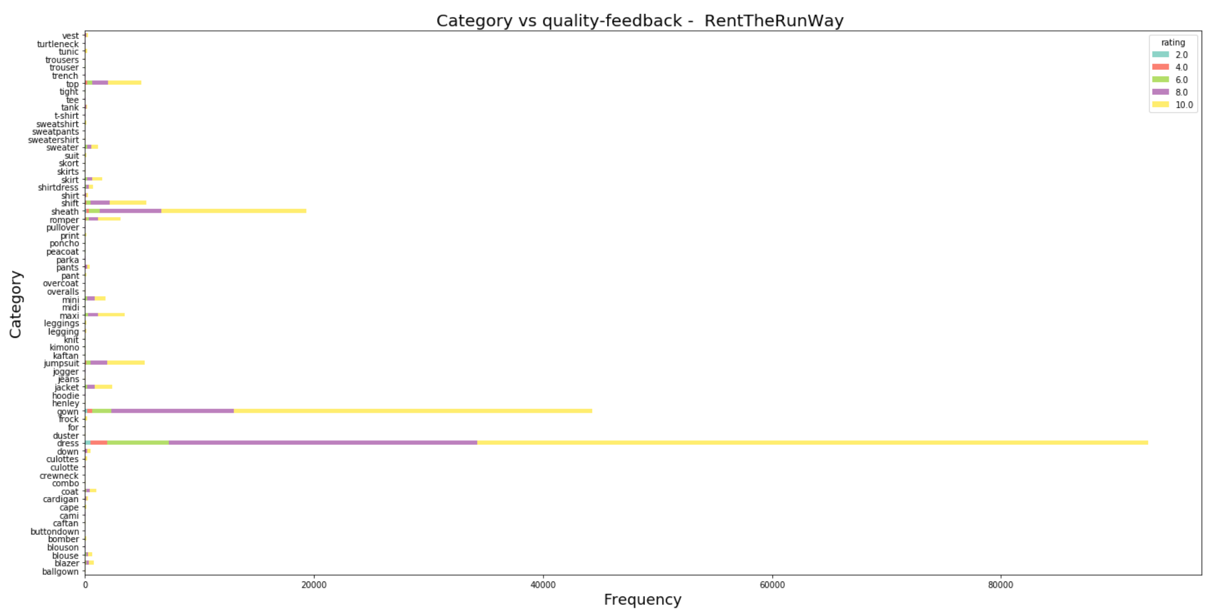


In [73]:
```
cat_len_norm = norm_counts(cat_len)
cat_len_norm.drop(['fit'], axis = 1, inplace=True)
plot_barh(cat_len_norm, 'fit', cmap='Set3', norm=1)
```

```
/Users/sungen/Documents/Jupyter/anaconda3/lib/python3.7/site-packages/i
pykernel_launcher.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  del sys.path[0]
```

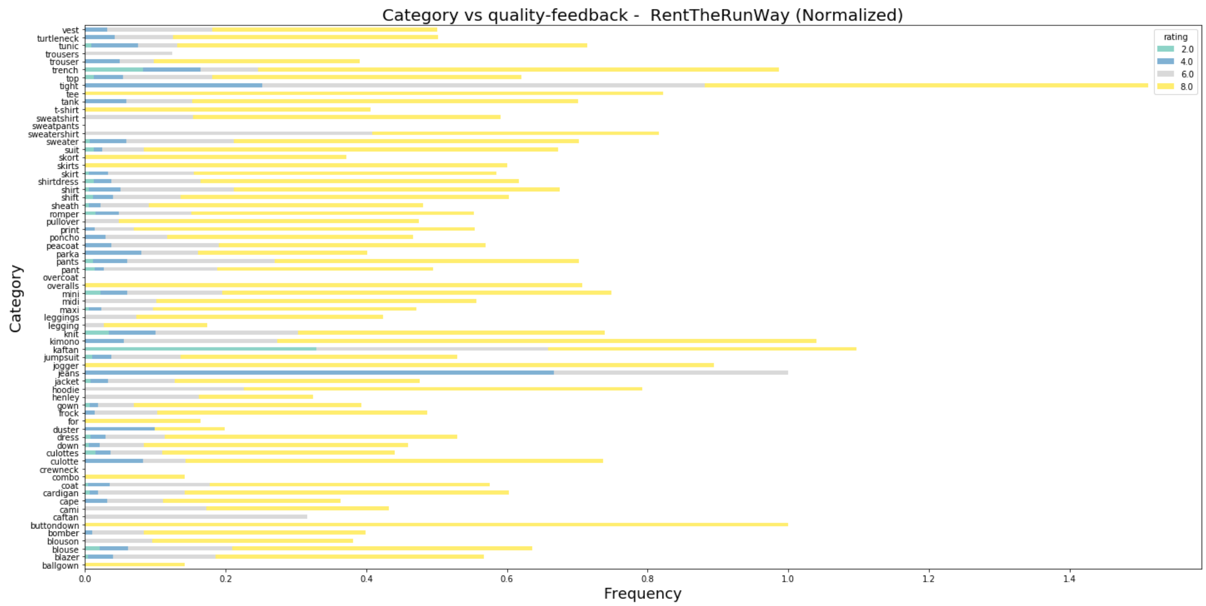


In [74]:
```
cat_quality = g_by_category['rating'].value_counts()
cat_quality = cat_quality.unstack()
plot_barh(cat_quality, 'quality', 'Set3', stacked=1)
```

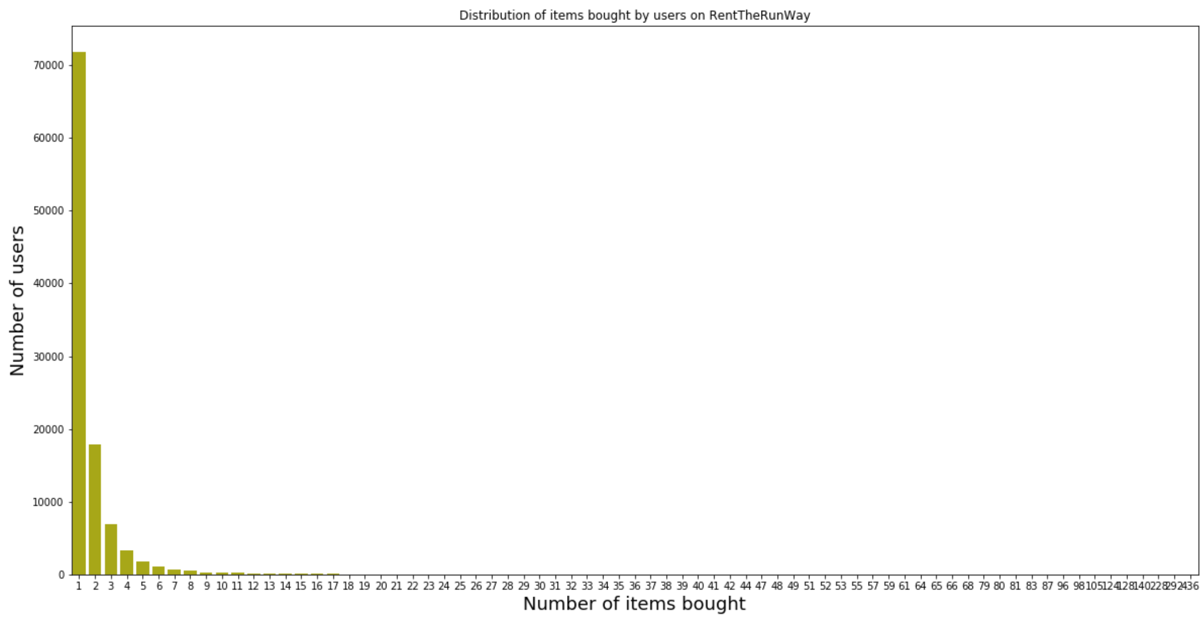


In [78]:
```
cat_quality_norm = norm_counts(cat_quality)
cat_quality_norm.drop([10.0], axis = 1, inplace=True)
plot_barh(cat_quality_norm, 'quality', 'Set3', stacked=1, norm=1)
```

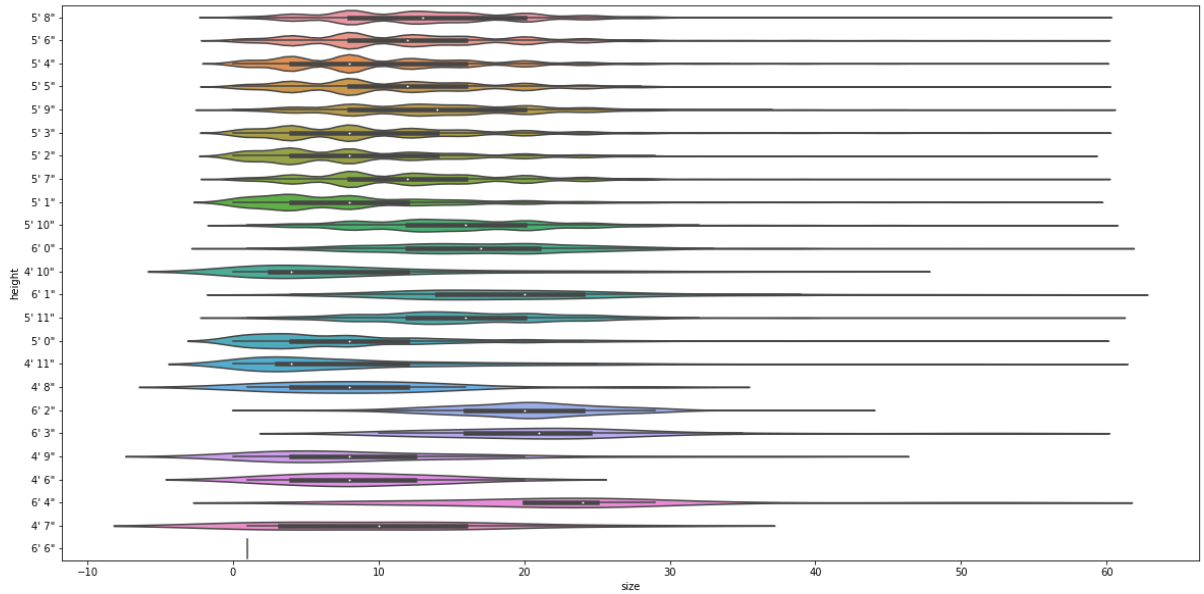
```
/Users/sungen/Documents/Jupyter/anaconda3/lib/python3.7/site-packages/i
pykernel_launcher.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  del sys.path[0]
```



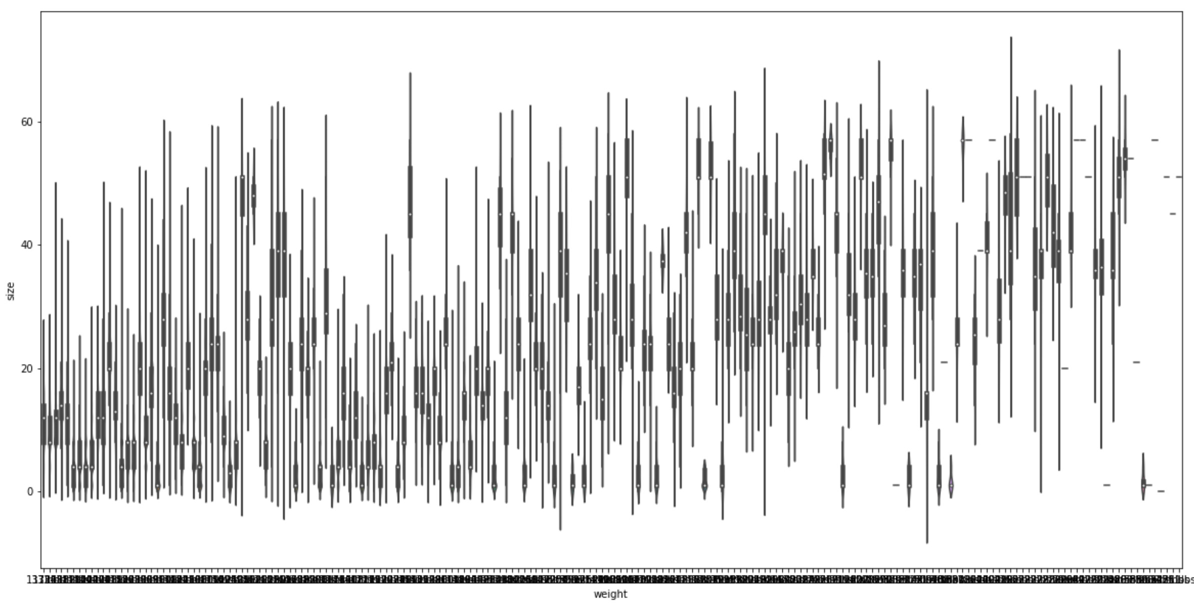
In [81]:
```
import seaborn as sns
items_bought = []
total_users = []
for i in range(min(mc_df.user_id.value_counts()), max(mc_df.user_id.valu
e_counts())+1):
    all_users = sum(mc_df.user_id.value_counts() == i)
    if all_users != 0:
        total_users.append(all_users)
        items_bought.append(i)
plt.xlabel("Number of items bought", fontsize = 18)
plt.ylabel("Number of users", fontsize = 18)
plt.title("Distribution of items bought by users on RentTheRunWay")
__ = sns.barplot(x=items_bought, y=total_users, color='y')
fig = plt.gcf()
fig.set_size_inches(20,10)
```



In [82]:
```
fig = plt.gcf()
fig.set_size_inches(20,10)
__ = sns.violinplot(x='size', y='height',data=mc_df, size = 20)
```



In [84]:
```
fig = plt.gcf()
fig.set_size_inches(20,10)
__ = sns.violinplot(y='size', x='weight',data=mc_df, size = 20)
```



Build the dataset

In [66]:
```
df = mc_df.dropna() # Disregard the missing items
df.shape
```

Out[66]: (146381, 15)

In [67]:
```
data = []
for index, row in df.iterrows():
    data.append(row)
```

In [68]:
```
data [9]
```

Out[68]:
```
fit                                                         large
user_id                                                    533900
bust_size                                                     34b
item_id                                                    130259
weight                                                     135lbs
rating                                                          8
rented for                                                wedding
review_text       This dress was absolutely gorgeous and I recei...
body_type                                                    pear
review_summary    Stunning dress, perfect for a New Year's Eve w...
category                                                    dress
height                                                      5' 6"
size                                                            8
age                                                            30
review_date                                       January 7, 2013
Name: 11, dtype: object
```

- Describe the dataset :

Use “renttherunway_final_data”

Number of customers: 105,508 Number of products: 5,850 Number of transactions: 192,544

Feature Description: item_id: unique product id weight: weight measurement of customer rented for: purpose clothing was rented for body type: body type of customer review_text: review given by the customer review_summary: summary of the review size: the standardized size of the product rating: rating for the product age: age of the customer category: the category of the product bust size: bust measurement of customer height: height of the customer fit: fit feedback user_id: a unique id for the customer review_date: date when the review was written

Transfer 'height' to numbers in cm

In [69]:
```
import string
punct = string.punctuation
sum_height = []
for d in data:
    if 'height' not in d:
        continue
    if d['height'] == None:
        continue
    t = d['height']
    t = [c for c in t if not (c in punct)] # non-punct characters
    t = ''.join(t) # convert back to string
    words = t.strip().split() # tokenizes
    d['height'] = int(words[0]) * 30.48 + int(words[1]) * 2.54
    sum_height.append(d['height'])
ave_hight = sum(sum_height) / len(sum_height)
```

In [70]:
```
ave_hight
```

Out[70]:
```
165.768155293403
```

Transfer 'weight' to numbers in lb

In [71]:
```
sum_weight = []
for d in data:
    if 'weight' not in d:
        continue
    if d['weight'] == None:
        continue
    t = [s for s in d['weight'] if s.isdigit()]
    t = int(''.join(t))
    d['weight'] = t
    sum_weight.append(d['weight'])
ave_weight = sum(sum_weight) / len(sum_weight)
print(ave_weight)
```

```
137.20987013341895
```

Transfer 'bust size' to numbers

In [72]:
```
bust = set()
for d in data:
    if 'bust_size' not in d:
        continue
    if d['bust_size'] == None:
        continue
    st = [s for s in d['bust_size'] if not s.isdigit()]
    st = ''.join(st)
    bust.add(st)
```

In [73]:
```
bust = list(bust)
bust.sort()
bust
```

Out[73]:
```
['a', 'aa', 'b', 'c', 'd', 'd+', 'dd', 'ddd/e', 'f', 'g', 'h', 'i',
'j']
```

In [74]:
```
onehot = {}
for i in range(len(bust)):
    initial = np.zeros(len(bust)+1)
    initial[i+1] = 1
    onehot[bust[i]] = initial
```

In [75]:
```
onehot
```

Out[75]:
```
{'a': array([0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]),
 'aa': array([0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]),
 'b': array([0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]),
 'c': array([0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.]),
 'd': array([0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]),
 'd+': array([0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.]),
 'dd': array([0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0.]),
 'ddd/e': array([0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0.,
0.]),
 'f': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0.]),
 'g': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.]),
 'h': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0.]),
 'i': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.]),
 'j': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.])}
```

In [76]:
```
for d in data:
    t = [s for s in d['bust_size'] if s.isdigit()]
    t = int(''.join(t))
    st = [s for s in d['bust_size'] if not s.isdigit()]
    st = ''.join(st)
    onehot[st][0]= t
    d['bust_size'] = onehot[st]
```

In [77]:
```
data[4]
```

Out[77]:
```
fit                                                                 fit
user_id                                                          734848
bust_size         [36.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0,...
item_id                                                          364092
weight                                                              138
rating                                                                8
rented for                                                         date
review_text       Didn't actually wear it. It fit perfectly. The...
body_type                                                      athletic
review_summary                        Traditional with a touch a sass
category                                                          dress
height                                                           172.72
size                                                                  8
age                                                                  45
review_date                                              April 30, 2016
Name: 5, dtype: object
```

In [78]:
```
random.seed(1)
random.shuffle(data)

train_data = data[:int(0.8*len(data))]
val_data = data[int(0.8*len(data)):int(0.9*len(data))]
test_data = data[int(0.9*len(data)):]

len(data), len(train_data), len(val_data), len(test_data)
```

Out[78]:
```
(146381, 117104, 14638, 14639)
```

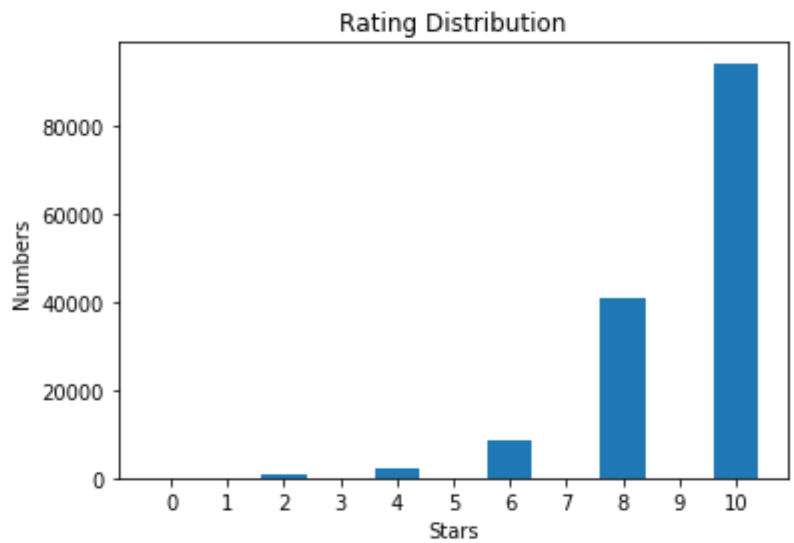
Rating distribution

In [32]:
```
num_star=[]
for i in range(11):
    numofstar = [int(d['rating']) == i for d in data if d['rating'] != N
one]
    num_star.append(sum(numofstar))
print(num_star)
print(sum(num_star))
```

```
[0, 0, 783, 0, 2205, 0, 8341, 0, 40761, 0, 94291]
146381
```

In [33]:
```
from matplotlib import pyplot as plt
X = [0,1,2,3,4,5,6,7,8,9,10]
Y = num_star
plt.xlabel("Stars")
plt.ylabel("Numbers")
plt.xticks([0,1,2,3,4,5,6,7,8,9,10],['0','1', '2', '3', '4', '5','6',
'7', '8', '9', '10'])
plt.title("Rating Distribution")
plt.bar(X, Y)
```

Out[33]: <BarContainer object of 11 artists>



In [34]:
```
nRatings = sum(num_star)
```

In [35]:
```
average = 0
for d in data:
    if d['rating'] != None:
        average += int(d['rating'])
average /= nRatings
print(average)
```

```
9.081984683804592
```

Remark： Highly imbalanced data. Most of the rating is fullmark (10 Point)

Users and items distribution

In [79]:
```
item_data = {}
item_index = {}
user_index = {}
user_data = {}
u_index = 0
i_index = 0
for r in train_data:
    if str(r['item_id']) + '|' + str(r['size']) not in item_data:
        item_data[str(r['item_id']) + '|' + str(r['size'])] = [r]
        item_index[str(r['item_id']) + '|' + str(r['size'])] = i_index
        i_index += 1
    else:
        item_data[str(r['item_id']) + '|' + str(r['size'])].append(r)

    if r['user_id'] not in user_data:
        user_data[r['user_id']] = [r]
        user_index[r['user_id']] = u_index
        u_index += 1
    else:
        user_data[r['user_id']].append(r)
```

In [80]:
```
len(user_data), len(user_index), len(item_data), len(item_index)
```

Out[80]: (66495, 66495, 26198, 26198)

Size Prediction

In [123]:
```
def feature(dataset):
    feat = [1]
    feat.append(dataset['height'])
    feat.append(dataset['weight'])
    feat = feat + list(dataset['bust_size'])
    return feat
```

In [124]:
```
X_train = [feature(d) for d in train_data]
X_valid = [feature(d) for d in val_data]
y_train = [d['size'] for d in train_data]
y_valid = [d['size'] for d in val_data]
```

In [125]:
```
X_train[:2]
```

Out[125]:
```
[[1,
  165.1,
  120,
  34.0,
  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],
 [1,
  162.56,
  115,
  36.0,
  0.0,
  0.0,
  1.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0]]
```

In [84]:
```
y_train[:10]
```

Out[84]:
```
[4, 4, 24, 4, 8, 1, 4, 8, 12, 4]
```

In [54]:
```
theta,residuals,rank,s = np.linalg.lstsq(X_train, y_train)
print(theta)
```

```
[-0.25687313 -0.11252349  0.31507325 -0.34904429 -1.0649248  -1.3383504
8
 -0.73047006 -0.24484903 -0.55436659  1.16470627 -0.68631815 -0.5062719
 -0.65753225 -1.46811342  2.45081446  1.41938696  1.95941587]
```

```
/Users/sungen/Documents/Jupyter/anaconda3/lib/python3.7/site-packages/i
pykernel_launcher.py:1: FutureWarning: `rcond` parameter will change to
the default of machine precision times ``max(M, N)`` where M and N are
the input matrix dimensions.
To use the future default and silence this warning we advise to pass `r
cond=None`, to keep using the old, explicitly pass `rcond=-1`.
  """Entry point for launching an IPython kernel.
```

In [114]:
```
import sklearn.metrics as sm
```

In [56]:
```
theta_Mat = np.matrix(theta)
X_train_Mat = np.matrix(X_train)
y_train_Mat = np.matrix(y_train)
X_valid_Mat = np.matrix(X_valid)
y_valid_Mat = np.matrix(y_valid)
```

In [57]:
```
y_train_pred = np.dot(theta_Mat, X_train_Mat.T)
MSE_train = sm.mean_squared_error(y_train_Mat, y_train_pred)
print('MSE_train =', MSE_train)
```

```
MSE_train = 16.697021350775483
```

In [58]:
```
y_valid_pred = np.dot(theta_Mat, X_valid_Mat.T)
MSE_test = sm.mean_squared_error(y_valid_Mat, y_valid_pred)
print('MSE_test =', MSE_test)
```

```
MSE_test = 16.816549710259217
```

Because different catagories have different size ranges, so we should do the regression based on the catagory.

Predict 'Fit'

Assign id for each category

In [89]:
```
category_count = defaultdict(int)
total_categories = 0
for d in data:
    if 'category' not in d:
        continue
    c = d['category']
    total_categories += 1
    category_count[c] += 1
counts = [(category_count[c], c) for c in category_count]
counts.sort()
counts.reverse()
categories = [c[1] for c in counts]
category_id = dict(zip(categories, range(len(categories))))
category_set = set(categories)
```

In [90]:
```
counts[:10]
```

Out[90]:
```
[(70474, 'dress'),
 (33278, 'gown'),
 (14691, 'sheath'),
 (4039, 'shift'),
 (4019, 'jumpsuit'),
 (3780, 'top'),
 (2600, 'maxi'),
 (2447, 'romper'),
 (1871, 'jacket'),
 (1417, 'mini')]
```

In [91]:
```
category_id['dress']
```

Out[91]:
```
0
```

In [161]:
```
from sklearn.linear_model import LogisticRegression

def train(data, c): # predict given a specific category
    try:
        random.seed(1)
        random.shuffle(data)

        train_data = data[:int(0.8*len(data))]
        val_data = data[int(0.8*len(data)):int(0.9*len(data))]
        test_data = data[int(0.9*len(data)):]

        len(data), len(train_data), len(val_data), len(test_data)

        X_train = [feature(d) for d in train_data]
        X_valid = [feature(d) for d in val_data]
        y_train = [d['size'] for d in train_data]
        y_valid = [d['size'] for d in val_data]

        clf = LogisticRegression(solver='lbfgs', multi_class='multinomia
l', max_iter=1000).fit(X_train, y_train)
        theta = clf.coef_

        y_train_pred = clf.predict(X_train)
        MSE_train = sm.mean_squared_error(y_train, y_train_pred)

        y_valid_pred = clf.predict(X_valid)
        MSE_test = sm.mean_squared_error(y_valid, y_valid_pred)

        return {
            'category': c,
    #         'theta': theta,
            'clf': clf,
            'MSE_train': MSE_train,
            'MSE_test': MSE_test,
        }
    except ValueError:
        print(c)
        print(len(data))
```

train regressor for each category

In [168]:
```
data_c = {}
data_train = data[:int(0.9*len(data))]
for d in data[:int(len(data_train))]:
    if d['fit'] != 'fit':
        continue
    c = d['category']
    if c not in data_c:
        data_c[c] = []
    data_c[c].append(d)
```

In [169]:
```
# train(data_c['dress'], 'dress')
clfs = {}
for c in categories:
    if c in data_c and len(data_c[c]) > 0:
        clfs[c] = train(data_c[c], c)
```

```
/Users/czf/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mod
el/logistic.py:947: ConvergenceWarning: lbfgs failed to converge. Incre
ase the number of iterations.
  "of iterations.", ConvergenceWarning)
/Users/czf/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mod
el/logistic.py:947: ConvergenceWarning: lbfgs failed to converge. Incre
ase the number of iterations.
  "of iterations.", ConvergenceWarning)
/Users/czf/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mod
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ase the number of iterations.
  "of iterations.", ConvergenceWarning)
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ase the number of iterations.
  "of iterations.", ConvergenceWarning)
/Users/czf/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mod
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ase the number of iterations.
  "of iterations.", ConvergenceWarning)
/Users/czf/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mod
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ase the number of iterations.
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ase the number of iterations.
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/Users/czf/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mod
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kaftan
3
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ase the number of iterations.
  "of iterations.", ConvergenceWarning)
```

```
hoodie
5
overalls
5
for
4
skirts
4
jogger
3
caftan
2
sweatershirt
2
overcoat
1
crewneck
1
```

In [170]:
```
for c in clfs:
    print(c + " ", clfs[c]['MSE_test'])
```

```
dress  18.209353628943305
gown  18.094196804037004
sheath  20.300200803212853
shift  23.253061224489795
jumpsuit  16.917293233082706
top  14.876
maxi  18.53370786516854
romper  12.896969696969697
jacket  10.606837606837606
mini  9.242105263157894
skirt  17.094594594594593
sweater  12.271186440677965
coat  19.146341463414632
blazer  13.162790697674419
shirtdress  24.805555555555557
blouse  17.727272727272727
down  13.333333333333334
pants  14.368421052631579
vest  34.18181818181818
shirt  18.416666666666668
cardigan  15.0
frock  2.7
culottes  27.6
tank  64.5
tunic  28.142857142857142
suit  5.125
bomber  21.714285714285715
sweatshirt  20.0
leggings  23.333333333333332
print  17.714285714285715
legging  12.0
pant  21.6
cape  6.75
culotte  15.25
trouser  29.666666666666668
pullover  17.333333333333332
midi  33.333333333333336
knit  18.0
poncho  68.0
peacoat  32.5
kimono  100.0
turtleneck  18.0
trench  0.0
tee  36.0
tight  0.0
parka  16.0

---------------------------------------------------------------------------
----
TypeError                                 Traceback (most recent call l
ast)
<ipython-input-170-a42dcea9afd2> in <module>
      1 for c in clfs:
----> 2     print(c + " ", clfs[c]['MSE_test'])

TypeError: 'NoneType' object is not subscriptable
```

Using size and pred to get fit

In [178]:
```
data_dev = data[int(len(data) * 0.9):]
y_dev = [d['fit'] for d in data_dev]
pred = []
for d in data_dev:
    res = 'fit'
    c = d['category']
    if c in clfs and clfs[c] is not None:
        clf = clfs[c]['clf']
        y = clf.predict([feature(d)])
        if y > d['size'] + 10:
            res = 'large'
        elif y < d['size'] - 10:
            res = 'small'
    pred.append(res)
```

In [179]:
```
pred[:10], y_dev[:10]
```

Out[179]:
```
(['fit', 'fit', 'fit', 'fit', 'fit', 'fit', 'fit', 'small', 'fit', 'fi
t'],
 ['fit', 'fit', 'fit', 'fit', 'fit', 'fit', 'fit', 'fit', 'small', 'fi
t'])
```

In [180]:
```
def evaluate(y, pred):
    t_fit, f_fit, t_small, f_small, t_large, f_large = 0, 0, 0, 0, 0, 0
    correct = 0
    tot, tot_fit, tot_small, tot_large = len(y), 0, 0, 0

    for i in range(0, tot):
        if pred[i] == y[i]:
            correct += 1
        if pred[i] == 'fit': #fit
            if y[i] == pred[i]: t_fit += 1
            else: f_fit += 1
            tot_fit += 1
        elif pred[i] == 'small': #small
            if y[i] == pred[i]: t_small += 1
            else: f_small += 1
            tot_small += 1
        else:
            if y[i] == pred[i]: t_large += 1
            else: f_large += 1
            tot_large += 1

    precision_fit = t_fit / (t_fit + f_fit)
    precision_small = t_small / (t_small + f_small)
    precision_lager = t_large / (t_large + f_large)

    recall_fit = t_fit / tot_fit
    recall_small = t_small / tot_small
    recall_large = t_large / tot_large

    acc = correct / tot

    return {
        'acc': acc,
        'precision_fit': precision_fit,
        'precision_small': precision_small,
        'precision_lager': precision_lager,
        'recall_fit': recall_fit,
        'recall_small': recall_small,
        'recall_large': recall_large,
    }
```

In [181]:
```
evaluate(y_dev, pred)
```

Out[181]:
```
{'acc': 0.7186283216066671,
 'precision_fit': 0.7333474606201879,
 'precision_small': 0.2808022922636103,
 'precision_lager': 0.3007518796992481,
 'recall_fit': 0.7333474606201879,
 'recall_small': 0.2808022922636103,
 'recall_large': 0.3007518796992481}
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

Ignore the following part

In [102]:
```
X_train[0]
```

Out[102]:
```
[1,
 165.1,
 120,
 34.0,
 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]
```

In [107]:
```
from sklearn.multioutput import MultiOutputRegressor
from sklearn.neighbors import KNeighborsRegressor
```

In [108]:
```
knn = KNeighborsRegressor()
multiOutputRegressor = MultiOutputRegressor(knn)
```

In [109]:
```
multiOutputRegressor.fit(X_train, y_train)
```

Out[109]:
```
MultiOutputRegressor(estimator=KNeighborsRegressor(algorithm='auto',
                                                   leaf_size=30,
                                                   metric='minkowski',
                                                   metric_params=None,
                                                   n_jobs=None, n_neigh
bors=5,
                                                   p=2, weights='unifor
m'),
                     n_jobs=None)
```

In [110]:
```
pred = multiOutputRegressor.predict(X_dev)
```

In [118]:
```
def cal_MSE(pred, y, data):
    l1 = []
    l2 = []
    for i in range(0, len(data)):
        c = data[i]['category']
        c_id = category_id[c]
        l1.append(pred[i][c_id])
        l2.append(y[i][c_id])
    ret = sm.mean_squared_error(l1, l2)
    return ret
```

In [119]:
```
cal_MSE(pred, y_dev, val_data)
```

Out[119]:
```
110.79968028419184
```

In [122]:
```
multiOutputRegressor.get_params()
```

Out[122]:
```
{'estimator__algorithm': 'auto',
 'estimator__leaf_size': 30,
 'estimator__metric': 'minkowski',
 'estimator__metric_params': None,
 'estimator__n_jobs': None,
 'estimator__n_neighbors': 5,
 'estimator__p': 2,
 'estimator__weights': 'uniform',
 'estimator': KNeighborsRegressor(algorithm='auto', leaf_size=30, metri
c='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=
2,
                     weights='uniform'),
 'n_jobs': None}
```

In [ ]: