Milestone Report 1
Capstone 2
Predicting Styles from Street Fashion Data

Maia Paddock

04/05/2019

The fashion industry struggles from the unique problem that all of the merchandise is inherently visual. Unlike consumers buying electronics or home goods, the details on the performance and use of the items is frequently not as important as the aesthetic appearance of the item. Additionally, these aesthetics can be difficult to classify, as trends and consumer tastes change with time, location, and with different consumers. Therefore, the fashion industry has embraced machine learning as a way to tackle these complicated trends.

Manual classification of images is a time intensive task. Therefore, collecting and tagging datasets of fashion images with associated metadata of any type can be time-consuming. Many companies rely on user input to give them the metadata needed to train models for recommendation engines or to classify clothing.The Street Fashion Data Set collected for the paper Understanding Fashion Trends from Street Photos via Neighbor-Constrained Embedding Learning[1] circumvented this challenge by taking data from the website Chictopia[2]. The data from this website is well suited for machine learning applications. Each image on this website visually similar, consisting of a full body image of a single person standing in front of a (generally urban) background. Additionally, each image comes with associated metadata on the outfit. Some of this data is created by the users themselves, such as tags describing the fashion pictured in the image, and some of the data is generated by the website, such as the time the image was uploaded. This collection of almost 300,000 images and their associated metadata is large enough to conduct extensive analysis.

The metadata of the street photos includes the user name, the name of the associated photo, the location, the date it was uploaded, and two categories of user-added data: tags and styles. Styles is the more abstract of these two categories, including entries such as “classic”, “everyday”, “fall”, “chic”, “comfortable”, “beach”, and “trendy.” These style descriptors give an insight into the mind of the users and how they would classify their own outfits. The tags on the outfits are more concrete descriptors, including brand names, colors, and types of clothing, such as “dress” or “heels.”

---

[1] Understanding Fashion Trends from Street Photos via Neighbor-Constrained Embedding Learning by X. Gu, Y. Wong, P. Peng, L. Shou, G. Chen, M. Kankanhalli http://doi.org/10.1145/3123266.3123441

[2] http://www.chictopia.com/

There are many different analyses that can be performed with this dataset. The location data suffers from not being dense or evenly distributed, meaning that it would be difficult to create a classification model to predict the location of an image based on the properties of the image and other metadata. However, exploratory data analysis could still show interesting trends related to location. The dataset covers a period of 8 years, from 2008 through 2015. While the data is most likely not dense enough across time to be used for any time projection, looking for any cyclic behaviors in the tags and styles could provide helpful information. The most interesting and useful categories of metadata on this dataset are the styles and tags. These two types of descriptors for the images provide a wealth of possibilities for analysis of these images and the dataset as a whole.

This dataset lends itself to two classification problems: the classification of the images by tags and by styles. Image recognition methods will be tested to create a model which returns tags for each image based on the image itself. Tags are mainly colors and items of clothing, and therefore with the correct model should be able to be found using only the images. Building from this analysis,
the combination of tags and the images themselves can be used to create another classification model to return the overall style of the image. This model will use both the visual data and the pre-existing tags on the image, hoping to use the correlations between the frequency of different tags and styles. For example, the tag "sandal" would likely be more correlated with the styles "summer" and "casual" than "winter" or "formal." Exploratory data analysis will show if other variables included in the metadata should be tested in the models as well to improve performance.

This analysis should provide trained predictive models for classifying fashion images. These models could form the basis of recommendation systems for fashion retail by assisting in the feature classification of clothes. If both classification models perform successfully, they could be combined into a pipeline that automatically returns tags and styles for any given image. Therefore, these models can provide both concrete and abstract features of clothes, potentially creating a broad amount of easy to manipulate, human-readable data from only images.

Data was obtained from the street fashion dataset found at https://zenodo.org/record/833051. The complete files contained 293,105 data points, originally crawled from the website Chictopia. There are approximately 27 Gb of image data, split into 27 files of 1 Gb each. The metadata for all of the images is contained in a separate csv file, with the image names as one of the columns to facilitate matching the correct row to the corresponding image. Additionally, a set of pre-cleaned data that was used in the paper referenced above is available for download. However, I did not choose to use this pre-cleaned data set as it would limit my investigation.

The metadata was cleaned first, before the images were addressed. The first step in cleaning the metadata was the remove all null entries from the users, picture name, location, and time categories. This removed approximately 9000 entries that had null entries in one of those four categories. Next, the time column was converted to a pandas datetime object in order to make working with times less complicated. The times in this column included only day, month, and year, therefore time zones were not considered or added to the data based on location.

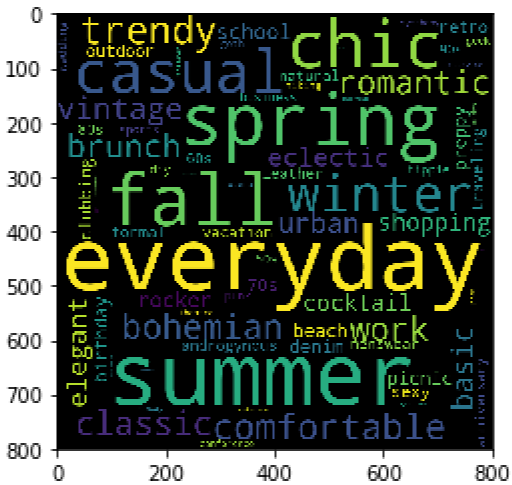
The next challenge was the clean and separate the tags and styles categories. The original metadata included all of the tags in a single column and all of the styles in another single column. These had to be split into different columns for each of the separate styles and tags. For example, an original entry in the styles column was "chic, beach, summer," which had to be split into three columns, style_0, style_1, and style_2, each of which held one of the words. Almost all of the entries had at least two styles listed, and approximately two-thirds of the data had three styles listed. None of the entries had more than three styles. To standardize the styles, all styles with more than one word were removed from the data.

Tags were far more difficult to clean for multiple reasons. While most entries included three styles, the number of tags on an entry ranged from one to seventeen. Initially, these were split from a single tag column into columns tags_0 through tags_16. Less than 1.5% of the total non-null tag data was included in the last seven columns, therefore these were dropped to help with processing time when looping through all of the data. Adding another challenge to cleaning the tag data, the tags were less standard and more variable than the styles. Brand names were included in the tags, leading to many multiple-word entries and more variable ways of expressing the same idea. The brand names had to be removed from the data because they would make the task of training a classifier based on the images much more difficult. The goal is a classifier that can tag colors and types of clothing. Therefore, for example, having different categories for "dress", "ASOS dress", and "Forever 21 dress" would add more confusion to the model and take away information that could be used to better classify dresses. Initially, I attempted to use the package Spacy to perform Named Entity Recognition (NER) and strip the brand names from each of the tags. However, I was only able to get an NER that could recognize and remove less than half of the brand names. By looking at the first few hundred entries in the dataframe, I was able to determine that a far more effective way to remove the brand names would be to simply keep only the last word of any phrase. Therefore, entries such as "Forever 21 dress" would be simplified to "dress", keeping only the data that I wanted. There are a few drawbacks to this method, but overall it was much more successful than using NER. One drawback is that it did not catch all brand names, because some brand names were tagged as a single word. Additionally, this method got rid of some useful data, for example "purple dress" was simplified to "dress", removing the color information that could be useful as a tag. The way to fix this would have been to split each entry down to a single word, creating more tag columns, and then applying an effective NER to remove the brand names. However, as I could not find an NER that could remove enough brand names to make this a viable option, I settled with keeping only the final word of each tag.

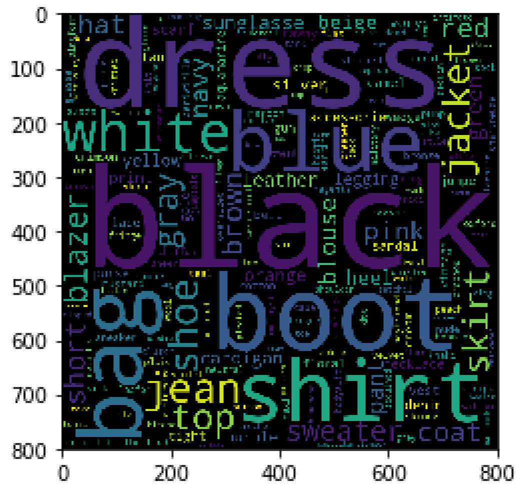
After these cleaning steps were completed, I saved the data to a new separate csv file that could be loaded to perform exploratory data analysis and statistical analysis. Just as with the data cleaning, I knew that performing EDA on the tags and styles would be the most difficult part of the process. Therefore, I started with looking at the user names and locations of the pictures. There were 3150 unique locations listed in the data, almost 900 of which are only mentioned once in the data. The majority of the locations are listed less than 12 times. Therefore, it is unlikely that locations will be useful in the model as the data is too sparse. The most listed location was unsurprisingly Los Angeles, CA, with almost 16000 entries.

There are 4976 unique users included in the data, each uploading a median of 20 images. A small number of users were responsible for a large amount of the data, with approximately 100 users uploading over 1000 images each. The most active user uploaded 8672 images. While it is possible that these users are individuals, it is likely that some of these users were in fact fashion photographers who uploaded photos of people other than themselves. The inclusion of fashion photographers in the data might influence the correlation between the user and the styles of their clothing.

Analysing the tags and the styles was a multistep processes. The first part of the process was to understand the compositing of the tags and styles using a word cloud. These word clouds allowed me to see that the data was in fact not fully cleaned. There were in fact some entries that contained the string “nan” instead of just being set to none, and these had to be removed. Next, I had to figure out how many of each of these tags and styles could be used for the analysis. The median value for the number of times a tag appeared was one. This clearly is not useful for a classification problem, where multiple instances of the tag would be necessary in order to train and test the classifier. Therefore, I made the somewhat arbitrary decision to cut on tags that appeared more than 100 times. This cutoff number can be adjusted during training to include more or less tags based on the performance of the classifier. Given this cutoff, there are 258 tags that appear more than 100 times. Any tags that did not correspond to these 258 words were removed from the data, and the data was reshaped so that there were no null tag values and it could be used in a classifier. The same process was repeated for the styles, leaving 68 styles with more than 100 occurrences. The word clouds for the styles and tags are shown below.



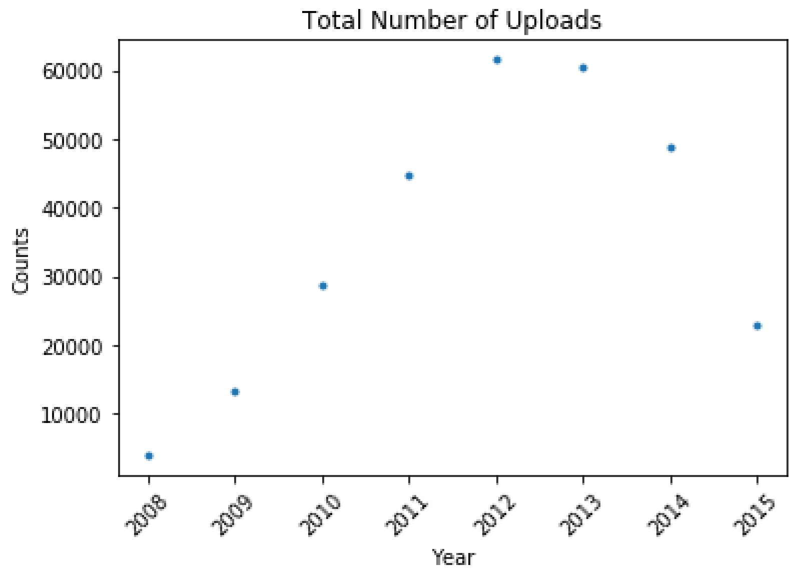
Word Cloud of Styles

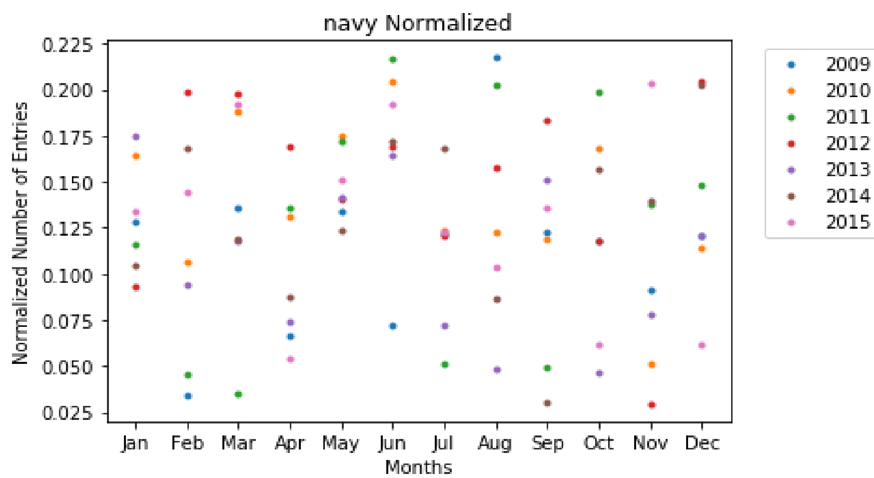


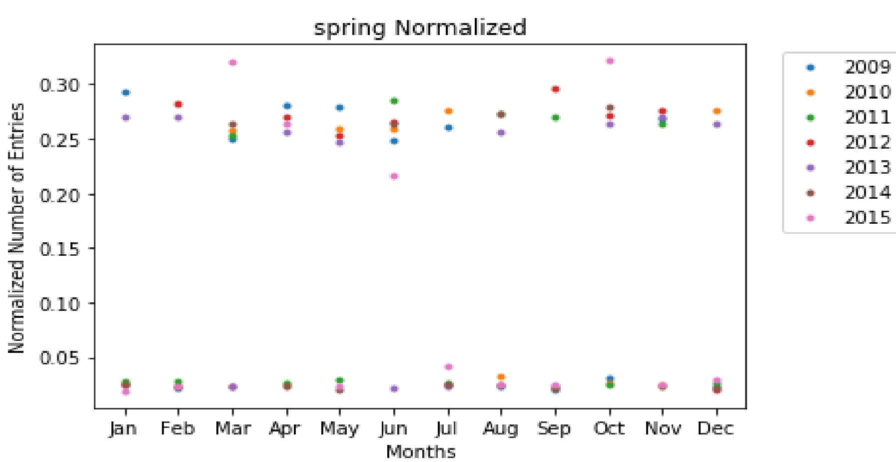
. Word Cloud of Tags

The next part of the exploratory data analysis was to see if the time data could be useful in the classifiers. The data covers eight years, from 2008 to 2015. Despite modelling the style and tag data in many ways, I was unable to find any trends in the data across years or any cyclic nature to the data by month. There are a few possible reasons for this. The first is that the data covers a large enough range of locations where seasonal differences would be washed out by the differences in climate at the difference locations. For example, users in Los Angeles would be likely to be able to wear shorts every month of the year, while users in New York City could only wear shorts June through August and users in Australia could only wear shorts in December through February.

When looking at the time data, an important step was to normalize all of the data so that I was graphing the percent of entries each month or year that contained a certain style or tag, not the number of entries. Graphing the total number of entries washed out any trends in favor of the much larger and more apparent trend of how many images were uploaded to the website in a given month or year. Overall, the data contains a rising number of submissions from 2008 to 2012 and a falling number of submissions from 2012 to 2015. Additionally, normalizing the data against the total number of entries per month did not reveal any trends in the top ten tags and styles.


Total Number of Uploads
Counts
Year
10000
20000
30000
40000
50000
60000
2008
2009
2010
2011
2012
2013
2014
2015


navy Normalized
Normalized Number of Entries
Months
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
2009
2010
2011
2012
2013
2014
2015


spring Normalized
Normalized Number of Entries
Months
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
2009
2010
2011
2012
2013
2014
2015

Statistical analysis for categorical data is tricky. I chose to perform a simple chi squared test to see if there was a statistically significant relationship between tags and styles that could potentially be exploited to build a model predicting styles using both tags and the images. The idea behind this model is that certain tags would correspond more closely to certain styles and that adding the tags as part of the training data on top of the images would improve the performance of classifying styles. I tested the null hypothesis that there is no statistically significant correlation between the tag “shorts” and the styles “summer” and “winter” and the null hypothesis that there is no statistically significant correlation between the tag “coat” and the styles “summer” and “winter”. There were 12638 occurances of the tag “shorts” and 12126 occurence of the tag “coat.” The percentages of each entry containing “summer” or “winter” also containing “shorts” or “coat” is shown in the table below.

	Summer	Winter
Shorts	7.25%	1.10%
Coat	1.30%	13.16%

Visually, this data looks to show the expected correlation. Tags of the summer associated “shorts” do in fact occur more on images that have been labeled as a summer style than a winter style. Tags of the winter associated “coat” also occur more on images that have been labeled with a winter style than a summer style. I completed this statistical analysis by performing a chi squared test to make sure this value was in fact statistically significant.

I was able to soundly reject both null hypotheses: summer and shorts are correlated more than winter and shorts with a chi squared value of 423 and winter and coats are correlated more than summer and coats with a chi squared value of 2126. As there is only one degree of freedom in each problem, these chi squared values correspond to p values of much less than 0.001, showing that each null hypothesis can be soundly rejected. Completing chi squared tests of this type for every potential pairing of tags and styles would take a long time, but this small investigation works as a proof of concept that there are meaningful relationships between the tags and the styles on the same images that could be used to classify the styles.

At the end of this process, the data is cleaned and ready to be used to classify the images. There was very little analysis or wrangling necessary for the images at this stage, as they all appear to be a very standard layout and format. Image manipulation will of course be a part of the next stage of the process as they will need to be broken down into matrix form, but given an initial visual inspection I do not foresee any difficulties with this process.