Prediction of Flickr Image Popularity

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Abstract

- Introduction and Problem Definition
  - Social Media Flickr Prediction (SMP) dataset
  - Given a photo (a.k.a. post) from a user, the goal is to automatically predict the popularity of the photo
- Model
  - Data Collection
  - Feature Selection

Feature		Correlation
Photo	Title Length	0.2283
	Description Length	0.2405
	Comment Count	0.3991
	View Count	0.3219
	Tag Count	0.3419
	Group Count	0.3220
	Favorite Count	0.3633
	avgMemberCount	-0.0096
	avgPhotoCount	-0.0002
User	Average View	0.5564
	Group Count	0.1762
	AvgMemberCount	0.6219
	Follower	0.0210
	Contact	-0.1566
	Photo Count	-0.3169

Abstract

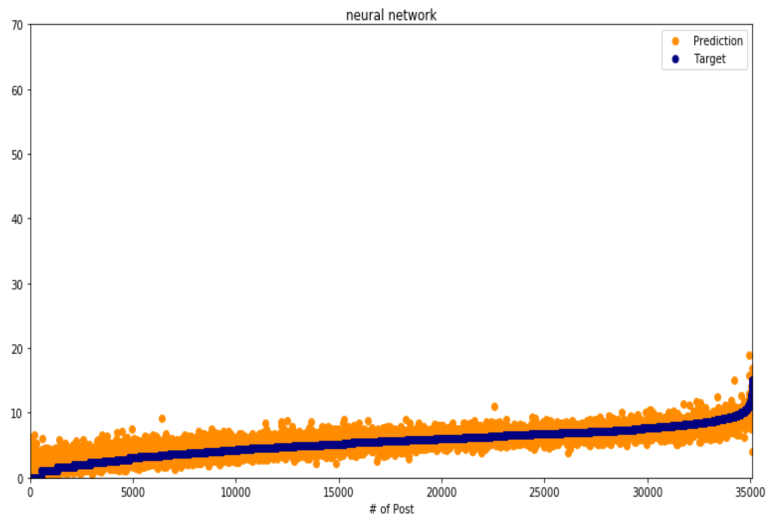
- Model(Cont.)
  - Text Feature

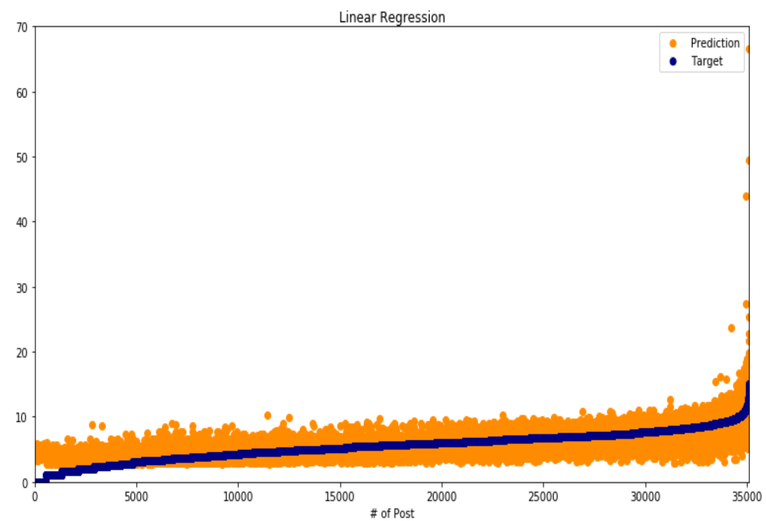
    use co-occurrence matrix to calculate the relationship of each tags.

$$F = (C \times q) \times \mathrm{idf}$$

  - Model Training

Model	MSE
Neural Network	0.52335
Linear Regression	2.42311





Abstract

- Model(Cont.)
  - Model Training

Neural Network Model	MSE
Input_dim=15 Hidden Layer Dense=120 Epoch: 100	0.52335
Epoch=200	0.48409
Input_dim=11	0.53500
Hidden Layer Dense=150	0.51467

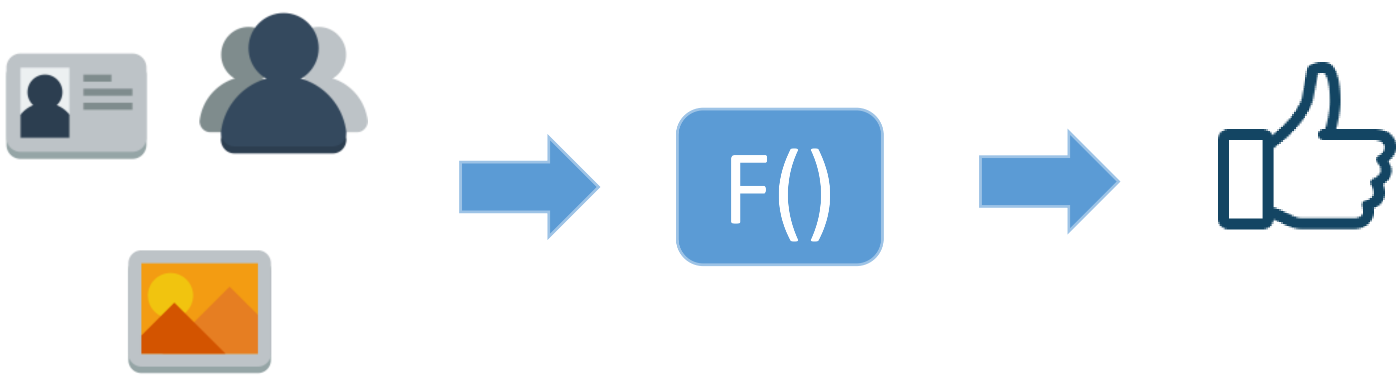
- Conclusion
  - Add more features: Textual feature, Image feature
  - Train different types of features separately
  - Use more complex model to reduce error

Outline

- Introduction
- Feature Selection
- Data Collection
- Method – Text Feature
- Model training
- Conclusions

Introduction and Problem Definition

- Popularity Prediction: Flickr
- Given a photo (a.k.a. post) from a user, the goal is to automatically predict the popularity of the photo
- Supervised Regression task
- Training data(Comment, View..) & Label data(Popularity Score)



Feature Selection

Numeral Feature	
Photo	Number of Comment
	Number of View
	Number of Favorites
User	Number of Followers
Group	avgMemberCount
	avgPhotoCount
	avgPostCount
	avgViewCount
	Group's tag

Textual Feature	
Photo	Tag
	Title
	Description

Reference. On the Prediction of Flickr Image Popularity by Analyzing Heterogeneous Social Sensory Data Sensors (Basel). 2017

Data Collection

Context

App Garden

建立應用程式 | API 說明文件 | Feeds | 什麼是應用程式園地?

Flickr API 由外部開發商用於非商業用途。商業用途可能優先安排。

首先閱讀這些：

- 開發人員指南
- 概要
- 編碼
- 使用者認證

- 日期
- 標籤
- URL
- 大頭貼

- Flickr API 使用條款

- API Key
- 開發商郵寄清單

相片上載 API

- 上載相片
- 取代相片

API 方法

activity

- flickr.activity.userComments
- flickr.activity.userPhotos

auth

- flickr.auth.checkToken
- flickr.auth.getFrob
- flickr.auth.getFullToken
- flickr.auth.getToken

auth.oauth

- flickr.auth.oauth.checkToken
- flickr.auth.oauth.getAccessToken

blogs

- flickr.blogs.getList
- flickr.blogs.getServices
- flickr.blogs.postPhoto

- people
  - people.getInfo
  - people.getPhotos
- groups
  - groups.getInfo
- photos
  - photos.getInfo
  - photos.getAllContexts
  - photos.getFavorites
- photos.comments
  - photos.comments.getList

userID	photoID	numberOfComment	numberOfView	numberOfTag	postDate	hasPeople	numberOfGroups	numberOfFavorites	NumberOfUploadPhoto	avgNumberOfMembers	avgNumberOfPhotos
7130511@N02	404831301	8	3195	4	1172601018	0	13	4	2641	4654	86598
7130511@N02	404831308	151	54183	21	1172601018	0	13	145	2641	7082	122845
7130511@N02	404831314	23	4499	12	1172601018	0	22	29	2641	19618	484996
7130511@N02	404862320	9	2374	3	1172603118	0	12	2	2641	3673	72021
7130511@N02	404884213	32	5441	14	1172604636	0	34	27	2641	13995	343553
7130511@N02	404884217	35	2225	12	1172604636	0	19	14	2641	5475	114383
7130511@N02	404893650	30	4960	8	1172605246	0	14	69	2641	6480	111534
7130511@N02	404896718	16	2446	10	1172605434	0	27	2	2641	8451	196951
7137783@N07	405343246	7	530	5	1172636373	0	6	1	5418	4169	57150
7211125@N08	405453022	0	72	2	1172645361	0	0	0	1204	4169	57150
7211125@N08	405453025	0	56	2	1172645361	0	0	0	1204	4169	57150
7211125@N08	405453026	0	54	2	1172645361	0	0	0	1204	4169	57150
7211125@N08	405453027	0	49	2	1172645362	0	0	0	1204	4169	57150
7211125@N08	405453029	0	48	2	1172645362	0	0	0	1204	4169	57150
7211125@N08	405453031	0	63	2	1172645362	0	0	0	1204	4169	57150
7218238@N08	405972460	7	241	2	1172689864	0	0	2	1564	4169	57150
7158589@N06	406396083	0	429	4	1172721434	0	21	5	13314	6990	139432

Data Collection

Pearson Score

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Data Collection

Missing Data

- Training data: 351,109
- Missing data: 38,046

1. Photo is deleted.
2. User is not found.

pid	uid	postdate	commentcount	haspeople	titlelen	deslen	tagcount	avgview	groupcount	avgmembercount
1373	3@N58	1172601018	0	0	37	243	4	818.11	909	8139
1374	3@N58	1172601018	0	0	22	103	21	818.11	909	8139
1375	3@N58	1172601018	0	0	9	35	12	818.11	909	8139
1376	3@N58	1172603118	0	0	10	95	3	818.11	909	8139
1378	3@N58	1172604636	0	0	18	44	14	818.11	909	8139
1379	3@N58	1172604636	0	0	15	22	12	818.11	909	8139
1380	3@N58	1172605246	0	0	14	123	8	818.11	909	8139
1381	3@N58	1172605434	0	0	16	87	10	818.11	909	8139
6476	6@N39	1172636373	0	0	16	30	5	176.58	160	6593
46169	41@N7	1172645361	0	0	13	0	2	22.02	18	2879
46170	41@N7	1172645361	0	0	14	0	2	22.02	18	2879
46171	41@N7	1172645361	0	0	14	0	2	22.02	18	2879
46172	41@N7	1172645362	0	0	14	0	2	22.02	18	2879
46173	41@N7	1172645362	0	0	13	0	2	22.02	18	2879
46174	41@N7	1172645362	0	0	17	0	2	22.02	18	2879
50585	45@N89	1172689864	0	0	18	0	2	197.85	377	4493
22720	15@N25	1172721434	0	0	17	0	4	25.36	1066	4831
22721	15@N25	1172721434	0	0	27	0	8	25.36	1066	4831
6487	6@N39	1172768335	0	0	34	312	5	176.58	160	6593

Text Features

- Reduce computational complexity :
  - 150,000 tags in our training set
  - We consider tags used > 505 times (1003 tags in our training set match)

	A	B	C	D
996	estraperlo	508		
997	clubdelritm	508		
998	hernandosg	507		
999	elineartpho	506		
1000	400d	505		
1001	iso100	505		
1002	zoo	505		
1003	mamiya	505		
1004	cfr	504		

Text Features

- We can represent each image in our collection by the tags it contains.

$$F = (C \times q) \times \mathrm{idf}$$

- C : Tag co-occurrence matrix
- q : Number of tags in an image's tag list
- idf : $\log(n/n^{(t_j)})$, n: sum of tags

  $n^{(t_j)}$: number of images containing tag tj

Tag co-occurrence matrix

- Symmetric measures: We can use symmetric measures, like Jaccard coefficient, to induce whether two tags have a similar meaning.

$$J(t_i, t_j) := \frac{|t_i \cap t_j|}{|t_i \cup t_j|}$$

, Eiffel Tower->Tour Eiffel, Eiffel, France

- Asymmetric measures: It captures how often the tag ti co-occurs with tag tj normalized by the total frequency of tag ti.

$$P(t_j|t_i) := \frac{|t_i \cap t_j|}{|t_i|}$$

, Eiffel Tower->Tour Eiffel, Eiffel, France

Model training

- Training Dataset: 315,998
- Testing Dataset: 35,111
- Comparison Methods
    - Linear Regression
    - Neural Network
        - Input layer: dim=15
        - 2 hidden layer: Dense=120
        - Activation Function: relu
        - Loss function: MSE
        - Epoch: 100, batch_size: 32

Model training

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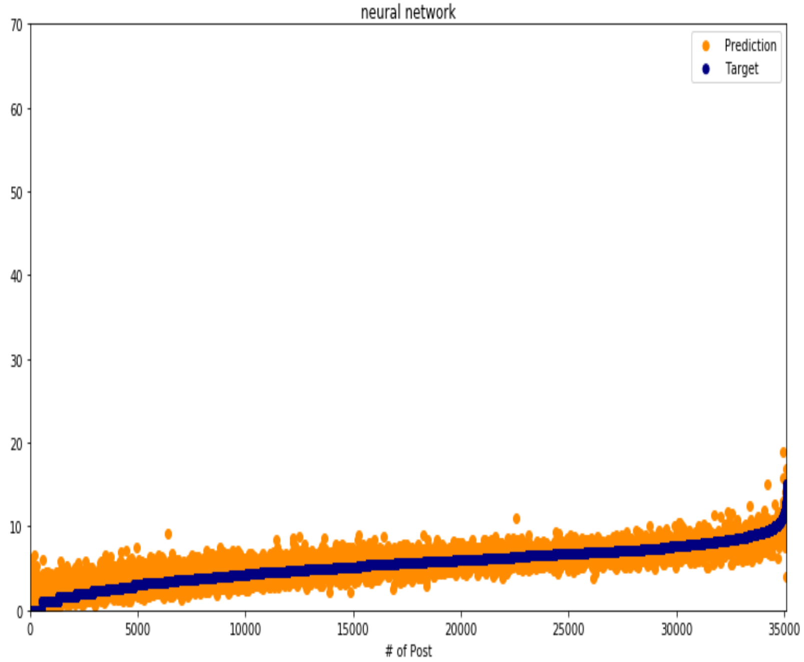

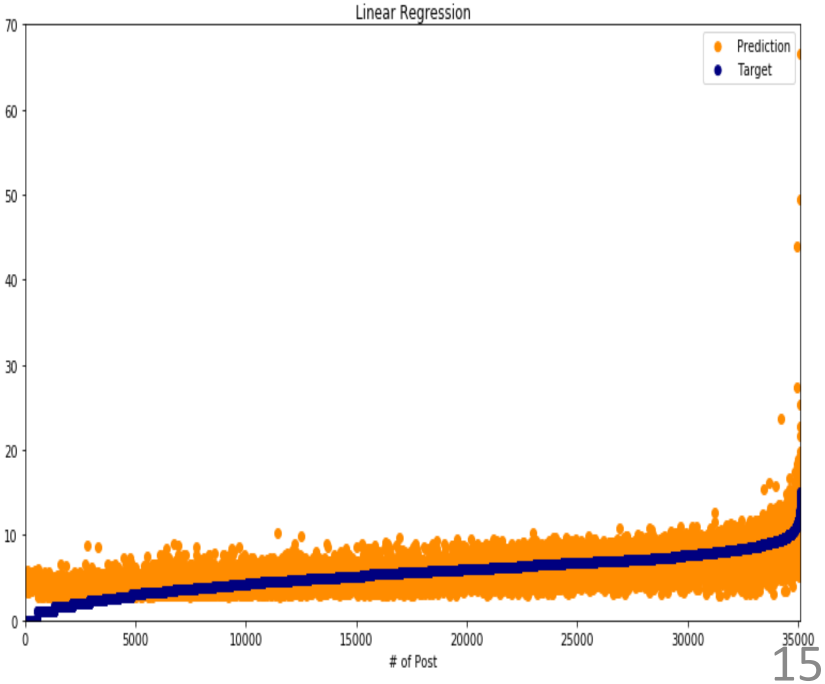

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- Train different types of features separately
- Use more complex model to reduce error