Affinity Filtering
A Novel Approach to Social Recommendation

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Except where otherwise indicated, this thesis is my own original work.

Riley Kidd
21 October 2012

Abstract

Social networks such as Facebook allow users to create a rich and verbose profile composed of both user specific interactions (such as comment and message passing, tags, likes) and user preferences (such as favourite movies and music, group memberships, page likes). These distinct components of a users profile can be leveraged to gauge their affinity with certain links and ultimately predict their explicit like preferences.

The goal of this thesis is to decipher which of these aforementioned affinity measures are truly predictive of a users like preferences.

The success of our predictions are evaluated using the machine learning algorithms of *Naive Bayes*, *Logistic Regression* and *Support Vector Machines*, results are compared to previous work using the state of the art social collaborative filtering technique of *Social Matchbox* as a baseline. The data set is sourced from a set of over 100 Facebook users and their interactions with over 39,000+ friends during a four month period.

Our analysis has shown that user interactions in themselves are not highly predictive of user likes, while user preferences are. We conclude by analysing a combination of the most predictive user preference measures, offer a summary of our work to date and propose recommendations for additional research in this area.

Contents

Chapter 1

Introduction

The Internet is becoming a network of people, providing a myriad of expanding social information and user driven content. Social presence on the web is continually expanding. With the emergence of services such as Facebook, Myspace, LinkedIn, Twitter and Google+, what defines a user and their online *user interactions* (such as comment and message passing, tags, likes) and *user preferences* (such as favourite movies and music, group memberships, page likes) is an expanding graph of rich social content.

The ultimate question we wish to address in this thesis then becomes: How can we leverage this user information to decipher which *user interaction* or *user preference* affinity features are most predictive of user likes?

We address this question by comparing and contrasting these different potential affinity relationships in our data against appropriate baselines and ultimately offer a combination of features which offers our best solution to the question posed above.

In this chapter we will outline the objectives of this research, summarise the contributions we have made and describe the lay out of this thesis.

1.1 Objectives

One issue present in this Facebook paradigm is discovering whether a user doesn't like an item, a users Facebook feed is comprised of activity between their friends, content, groups, etc giving an enormous scope of potential feed items. Facebook will only show feed items for users who have recently interacted with using their *Edge-Rank* [Sanghvi and Steinberg 2010] algorithm.

While many Facebook users have a friend count which is close to the human real word limit, known as the Dunbar number [Hill and Dunbar 2003], the *Edge-Rank* algorithm ensures user interactions are focused on a much smaller subset of their friends. Additionally, given the rate of posting, these top feed items are only displayed for a short amount of time. Coupled with the fact that Facebook allows users to explicitly like an item, but not dislike it - distinguishing between what a user does and does not like becomes difficult.

The primary objective of this thesis is to contrast and compare differing potential affinity features across *user interactions* and *user preferences*. Using state of the art machine learning concepts of *Naive Bayes* (NB), *Logistic Regression* (LR) and *Support Vector Machines* (SVM) compared with our appropriate baselines of *Social Matchbox* (SMB) and *Constant Classifiers*. With the aim of discovering which affinity features are most predictive or user likes.

Based on the insight that social inuence can play a crucial role in a range of behavioural phenomena [Granovetter 1978; Watts and Strogatz 1998] and that positive social annotations on search items add perceived utility to the worth of a result [Pantel and Haas 2012] we will also test using an exposure hold out technique, where data is only tested if some friend has already liked that item. Hence analysing the effect of exposure on our affinity features.

Finally, we will assess and compare the effect of combining successful individual affinity features found during our analysis.

1.2 Contributions

Our specific contributions made during this thesis show:

- Both *interactions* and *incoming \outgoing messages* posted between users are not more predictive then previously used SMB techniques.

- Each *user preference* affinity of *favourites* (such as favourite movies, music), *group* memberships (such as Australian National University and Students in Canberra) and *page* likes (such as Google Chrome and The Simpsons) outperformed our baselines.

- Combining both affinity types of *user interactions* and *user preferences* with an exposure limit resulted in a substantial improvement over previous techniques as the exposure increases.

- Combination of the advantageous affinity features briefly mentioned above gives the best results in our analysis.

Overall, we provide a methodology which improves upon previous work and offer an approach to combine positive affinity features.

1.3 Outline

The remaining chapters in this thesis are organised as follows:

- **Chapter 2**: We first outline appropriate background information for the reader. Including information pertaining to the source of our data set, mathematical notation used throughout this thesis, previous work in this area and our research approach and methodology.

- **Chapter 3**: In this chapter we discuss different affinity features for *user interactions* and the results of applying these features to NB, SVM and LR in comparison with our baselines.
- **Chapter 4**: A similar affinity feature analysis as above is applied, however the features we utilise are for *user preferences*.
- **Chapter 5**: In this chapter we discuss the effect of combining different affinity features based on results gained in the previous sections and propose an ideal affinity feature hybrid.
- **Chapter 6**: Finally, we draw the work done throughout this thesis to a conclusion and offer avenues for future work in this area.

All chapters combined, this thesis represents a novel approach to exploiting and analysing *user interactions* and *user preferences* affinity relationships to ascertain which features are most predictive of user likes and present an approach of combining these useful feature components into an effective classification paradigm.

Chapter 2

Background

In this chapter, we define the social network Facebook central to this study, the source of our data set, notation used throughout this thesis, our choice of classification algorithms and our testing approach and methodology.

2.1 Facebook

Facebook is the largest and most active social media service in the world (as of September 2012 it had more than 1 billion active users [**?**]). Facebook users can create a profile containing personal preferences and information including their favourite music, favourite movies, inspirational people, interests, age, birthday, etc and have friendships and interactions between other users.

The four main interactions between users are posts (posting something on a friends' wall), tags (being mentioned in a friends post or comment), comments (written data on a post) and likes (clicking a like button if a user likes a post or comment). The mediums for these interactions are across links (some URL), posts (some Facebook post), photos (some uploaded Facebook photo) and videos (some uploaded Facebook video).

Given the enormous scope of interaction and preference information available about each user, NICTA have developed an app capable of tracking and recording all pertinent user information. This app will be discussed in the following section.

2.2 Data Set

NICTA developed a Facebook app named *LinkR*. [1] This app collected information about users, their interactions and preferences as well as a subset of available information about their friends. The app tracked and stored this information for over 100 app users and their 39,000+ friends over a 4-month time period.

Exhaustive interaction and profile information could not be recorded for the app

[1] The main developer of the LinkR Facebook App is Khoi-Nguyen Tran, a PhD student at the Australian National University.

users friends and as such all analysis performed in this thesis was carried out exclusively on app users for whom we have full interaction and profile data.

The table below summarises the interactions data collected from both app users and their friends which is used during our subsequent analysis.

App Users	**Posts**	**Tags**	**Comments**	**Likes**
Wall	36,539	7,711	18,266	15,999
Link	5,304	-	5,757	6,566
Photo	4,933	28,341	8,677	8,612
Video	245	2,525	1,687	843
App Users and Friends	**Posts**	**Tags**	**Comments**	**Likes**
Wall	4,301,306	1,215,382	3,122,019	1,887,497
Link	678,612	-	693,930	995,214
Photo	1,268,816	9,620,708	3,431,321	2,469,859
Video	59,244	904,604	486,677	332,619

Table 2.1: Data records for interactions between users. Rows are the type of interaction, columns are the medium of interaction.

2.3 Notation

The mathematical notation utilised during this thesis is outlined below.

- N users U with an I-element user feature vector X where $X \in \mathbb{R}^I$ (alternatively if a second user is needed $Z \in \mathbb{R}^I$) and the length and components of I are uniquely defined for each affinity feature.
- A set of items V.
- A friend function $Friend_{u,z}$ which is *True* when users u and z are friends.
- A liked function $Liked_{u,v}$ which is *True* when user u likes item v.
- A relationship R between users where $R_{u,z}$ is uniquely defined for each affinity feature.
- An alters set A for each user u item v pair, based on some relationship R between other users z. Where $a_{u,v,r} = \{z | R_{u,z} \wedge Likes_{z,v}\}$.

  This alters set can be visualised in the figure below:
- An exposure E where $E_{u,v,z} = \sum_{z}^{N} Friend_{u,z} \wedge Liked_{z,v}$ where this exposure can be limited by some k with the condition $E_{u,v} >= k$.

  This exposure can be visualised in the figure below:
- A data-set D comprised of $D = \{(u, v, x) \rightarrow y\}$ where $u \in U$, $v \in V$ and the binary response $y \in \{0, 1\}$ where 0 represents a dislike and 1 represents a like.

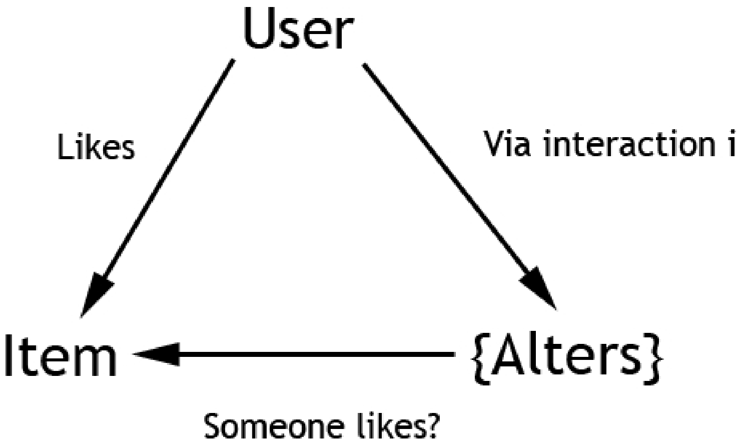
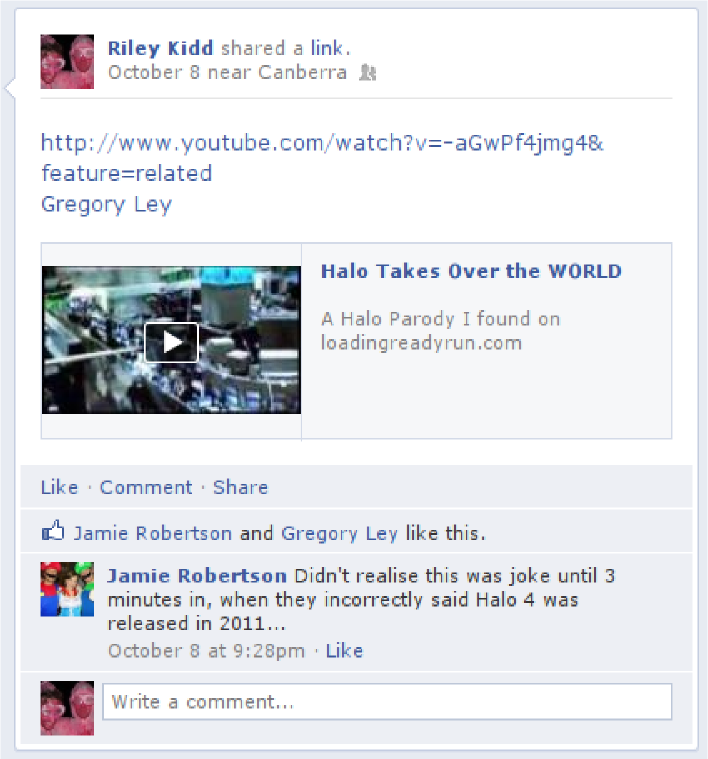


Figure 2.1: Alters paradigm. A user u likes some item m, a relationship $R_{u,z}$ is defined via some affinity i uniquely defined for each affinity feature, to create our set of alters A.



Riley Kidd shared a link.
October 8 near Canberra

http://www.youtube.com/watch?v=-aGwPf4jmg4&feature=related
Gregory Ley

Halo Takes Over the WORLD

A Halo Parody I found on loadingreadyrun.com

Like · Comment · Share

Jamie Robertson and Gregory Ley like this.

Jamie Robertson Didn't realise this was joke until 3 minutes in, when they incorrectly said Halo 4 was released in 2011...
October 8 at 9:28pm · Like

Write a comment...

Figure 2.2: Here we see an example of a link posted to a friends wall, which has subsequently been liked by two friends z. This demonstrates an exposure of 2 for this link m.

2.4 Affinity Features

Given the vast amount of potential affinity features available on Facebook, we need to break our features down into separate, distinct groups for testing purposes. Our two main groups will be *user interactions* and *user preferences*.

The individual components of these groups are displayed below: *User interactions*:

- *Interactions* : Posts, Tags, Likes, Comments.
- *Outgoing Messages* : Messages sent to other users.
- *Incoming Messages* : Messages received from other users.

User preferences:

- *Demographics* : Age, Gender, Hometown.
- *Favourites* : Activities, Books, Athletes, Teams, Movies, Music, Sports, Television, Movies, People, Interests.
- *Groups* : All groups a user has joined.
- *Pages* : All pages a user has liked.

Each of these affinity features will be discussed in detail under their separate sections of this thesis. During our analysis we will compare the predictiveness of each of these affinity features individually, as well as in combination.

2.5 Previous Work

Two general approaches to prediction in a social context are *content-based filtering* (CBF) [Lang 1995] which exploits item features based on items a user has previously liked and *collaborative filtering* (CF) [Resnick and Varian 1997] which exploits the current users preferences as well as those of other users.

Previous work defined the term *social* CF (SCF) [Noel 2011] which augments traditional CF methods with additional social network information, the results of this previous work and analysis using live user trials came to the conclusion that the approach of SMB provided the best results for this data set and as such will be used as a baseline in this thesis.

These methods of CBF, CF and SCF result in a user gaining some similarity measure between other users, while the affinity features we explore during this thesis are based on explicit *user interaction* and *user preference* features and result in different models and predictions based on our choice of feature selection.

2.6 Training and Testing

All evaluation is applied using 10 fold cross validation wherein the data is partitioned into 10 complementary subsets, 80% of these subsets are used for training while the remaining 20% are used for testing.

The training and testing process is repeated 10 times for each set of fold data. These results are then averaged to produce our estimates and standard error. The benefit of this method over repeated sub-sampling is all data points are used for both training and validatation.

2.7 Classification Algorithms

Each classification algorithm used in this thesis is passed the training data for each fold as outlined above. The classifier builds a model representation of the data and applies this model to the test set to classify each test item into either a like or a dislike.

All affinity feature analysis carried out in this thesis will be performed on the following classification algorithms:

2.7.1 Constant

The constant predictor returns a constant result irrespective of the feature vectors selected. Namely, this predictor returns 0 (false) regardless of the affinity feature represented by X. The most common result in our data set is $False$ and hence the $False$ predictor is displayed in all analysis, tables and graphs in this thesis.

2.7.2 Social Match Box

SMB is an extension of existing SCF techniques [Yang et al. 2011; Cui et al. 2011] which constrain the latent space to enforce users who have similar preferences to maintain similar latent representations when they interact heavily.

SMB uses the social regularization method which incorporates user features to learn similarities between users in the latent space which allows us to incorporate the social information of the Facebook data [Noel 2011].

This objective component constrains users with a high similarity rating to have the same values in the latent feature space, which models the assumption that users who are similar socially should also have similar preferences for items.

2.7.3 Naive Bayes

Naive Bayes is a basic probabilistic classifier which involves applying Bayes' theorem using strong conditional independence assumptions between each feature in X. During training each element i in the feature vector X is devised to contribute some evidence that this x_i belongs to either a like or dislike classification, during testing the class with the highest probability when applied to the model is the classification predicted.

With feature vector $f \in \mathbb{R}^F$ derived from $(x, y) \in D$, denoted as $f_{x,y}$. NB learns a conditional model of the form $p(C|F_1, \ldots, F_n)$ over a dependent class variable C conditioned on the feature variables $F_1, \ldots, F_n$. Applying both Bayes' rule and conditional independence assumptions the model can be rewritten as $p(C|F_1, \ldots, F_n) = p(C) \prod_{i=1}^{n} p(F_i|C)$.

Classification of our test vector is achieved by choosing the most probable class of either like (1) or dislike (0).

$$\text{classify}(f_1, \ldots, f_n) = \underset{c \in \{1,0\}}{\text{argmax}}\ p(C = c) \prod_{i=1}^{n} p(F_i = f_i | C = c).$$

2.7.4 Logistic Regression

Logistic Regression directly estimates parameters based on the training data assuming a parametric form of the distribution. LR predicts the odds of a feature vector X being either a like or a dislike by converting a dependent variable and one or more continuous independent variable(s) into probability odds.

With feature vector $f \in \mathbb{R}^F$ derived from $(x, y) \in D$, denoted as $f_{x,y}$. The linear predictor function $f(i)$ for a particular data point i is written as $f(i) = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_M x_{m,i}$, where $\beta_0, \ldots, \beta_M$ are regression co-efficients indicating the relative effect of a particular explanatory variable $x_{m,i}$ on the outcome.

The LR implementation used during this thesis is *LingPipe* [Alias-i. 2008. LingPipe 4.1.0. http://alias-i.com/lingpipe (accessed October 1 2011].

2.7.5 Support Vector Machine

The *Support Vector Machine* is a supervised learning machine based on a set of basis functions which help construct a separating hyperplane between data points. Training involves building the relevant hyperplanes which can then be used for testing. Each data point is classified as a like or dislike depending on which side of the hyperplane it falls.

With feature vector $f \in \mathbb{R}^F$ derived from $(x, y) \in D$, denoted as $f_{x,y}$. A linear SVM learns a weight vector $w \in \mathbb{R}^F$ such that $w^T f_{x,y} > 0$ indicates a like classification of $f_{x,y}$ and $w^T f_{x,y} \leq 0$ indicates a dislike classification.

The SVM implementation used during this thesis is *SVMLibLinear* [Chang and Lin 2011].

2.8 Evaluation Metrics

When evaluating the success of each afinnity feature at correctly classifying an item, the following metrics have been analysed.

- A *true positive* (TP) prediction refers to when the prediction correctly identifies the class as true.

- A *false positive* (FP) occurs when the prediction is true, but the true class was false.

- A *false negative* (FN) occurs when the prediction is false but the actual class is true.

These definitions can be visualised using the table below. Where:
y represents the true class value $y \in \{0, 1\}$: *actual*
$\hat{y}$ represents the class prediction $\hat{y} \in \{0, 1\}$: *prediction*.

		y	
		T	**F**
$\hat{y}$	**T**	TP	FP
	F	FN	TN

Table 2.2: Actual and prediction comparison table.

Accuracy relates to the closeness to the true value. In the context of our results, the accuracy refers to the number of correct classifications divided by the size of the data set.

$$\text{accuracy} = \frac{\text{number of correct classifications}}{\text{size of the test data set}}$$

Precision relates to the number of retrieved predictions which are relevant. In the context of our results, the precision refers to the number of TP predictions divided by the sum of the TP and FP predictions.

$$\text{precision} = \frac{\text{number of TP}}{\text{number of TP + number of FP}}$$

Recall refers to the number of relevant predictions that are retrieved. In the context of our results, recall refers to the number of TP predictions divided by the sum of the TP and FN predictions.

$$\text{recall} = \frac{\text{number of TP}}{\text{number of TP + number of FN}}$$

The f-score combines and balances both precision and recall and is interpreted as the weighted average of both precision and recall.

$$\text{f-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

The main metric we use for analysis, tabulation and graphing in this thesis is accuracy.

others have pointed out non social more important and we observe that too interactions give implicit networks of friendshipsprevious methods say if people interact alot then they will like the same things, we break it down into smaller implicit overlap of preferences

Chapter 3

Interactions

stronger affinity for what people say to you

This chapter is dedicated to analysing the different *user interaction* features present in Facebook.

The *user interactions* we examine in this thesis can be broken down into two distinct groups, interactions between users and messages sent between users.

bias for incoming having a stronger affinity

interaction filtering cant help when interactions dont exist - as soon as interactions we can exploit the information

3.1 User Interactions

There are a number of potential interaction mediums between users under the Facebook paradigm. These can be summarised into the following categories.

- **Direction**: The manner an interaction is received, either *Incoming* where a message is posted to some user or *Outgoing* where some user posts a message to another user. Interaction directionality has been shown to be highly reflective of user preferences [Saez-Trumper et al. 2011].
- **Modality**: The medium some user employs to interact with another user via either *Links*, *Posts*, *Photos* or *Videos*.
- **Type**: The style some user employs to interact with another user via either *Comment*, *Tag* or *Like*.

In this case, the I for out feature vector X is defined as the cross product of the above components where:

$$I = \{Incoming, Outgoing\} \times \{Posts, Photos, Videos, Links\} \times \{Comments, Tags, Likes\}$$

The alters of I can then be defined as all users who have interacted with or been interacted with the current user via some i. Each component of I is set to 1 if any of the alters defined by the current set i have also liked the current item M, otherwise it is set to 0.

Applying the feature vector described above to our classification algorithms we obtain:

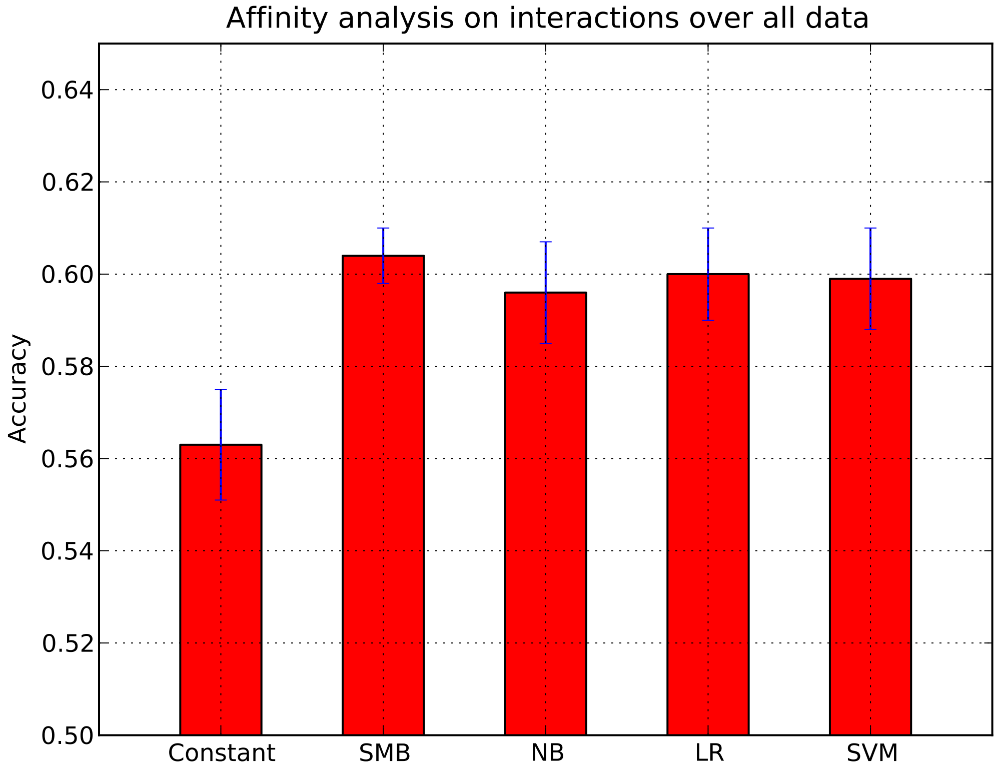


Figure 3.1: Accuracy results using *user interaction* features. Against all data *user interactions* do not outperform our baselines.

User Interactions are marginally outperformed by our SMB baseline, showing that relatively *User Interactions* do not improve upon classification.

One reason for this result could be we can not track information passing outside of Facebook, users who frequently interact could be real world friends and hence share information via email or word of mouth and not over Facebook.

Comparing *User Interactions* against our exposure curve we obtain:

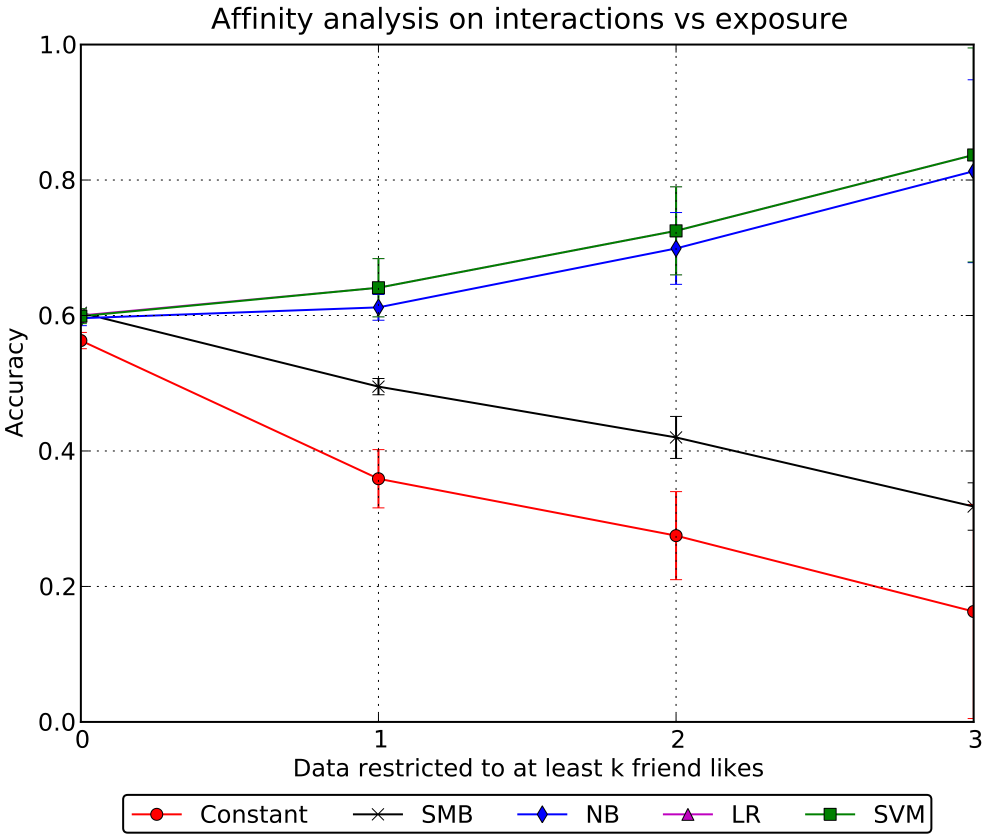


Figure 3.2: Accuracy results against exposure using *user interaction* features. *User interactions* provide a drastic improvement over our baselines as *k* increases, suggesting SMB is not always the best classifier.

We glean that as our data is restricted, the performance of our classifiers improves (note LR and SVM obtained the same results in this graph) over time. This graph shows that for *User Interactions* having one user liking an item is enough to improve upon our baselines classifiers.

3.2 Conversation

Given the nature of Facebook, it is possible for users to post or receive messages from other users.

These messages can be broken down based on their directionality, either *Outgoing* which are words sent to other users or *Incoming* which are words received from other users.

Based on our data set, the most commonly used words occur with a high frequency over our user base and can be seen in the table below:

Rank	Word	Frequency
1	:)	292,733
2	like	198,289
3	good	164,387
4	thanks	159,238
5	one	156,696
6	love	139,939
7	:p	121,904
8	time	106,995
9	think	106,459
10	see	103,690
11	nice	99,672
12	now	94,947
13	well	92,735
14	happy	84,381
15	:d	83,698
16	much	78,719
17	oh	77,321
18	yeah	76,564
19	back	76,032
20	great	70,514
21	going	70,447
22	still	68,245
23	new	67,430
24	day	65,579
25	come	63,837
26	;)	62,936
27	year	61,771
28	look	60,608
29	yes	59,774
30	want	59,514
31	tag	58,633
32	hahaha	57,448
33	also	56,414
34	need	55,921
35	make	54,949
36	sure	54,395
37	thank	54,112
38	people	53,211
39	miss	53,182
40	guys	52,855

Table 3.1: Top conversation content data for all users. We see very common words and online expressions have a high frequency in our data set.

There is clearly a high number of emotional and sentimental words being used on Facebook. This would imply interactions between real friends.

WUT - scott For messages the I of our feature vector X contains an element i for each of the top j most commonly used words based on the conversation content of all users.

The alters of I can then be defined as all users who have liked the current item M. Each component of I is set to 1 if any of the alters have used the current word j where $i = j$ with the user n, otherwise it is set to 0.

3.2.1 Outgoing

The first issue present is to determine the most predictive number of top *Outgoing* words j for use by our classifiers. Given the enormous size of potential messages and memory constraints in the testing environment we decided to test within a range of $\{100 - 1000\}$ with an incremental step size of 100 for each test.

The results of testing based on differing sizes of *Outgoing Words* can be seen below:

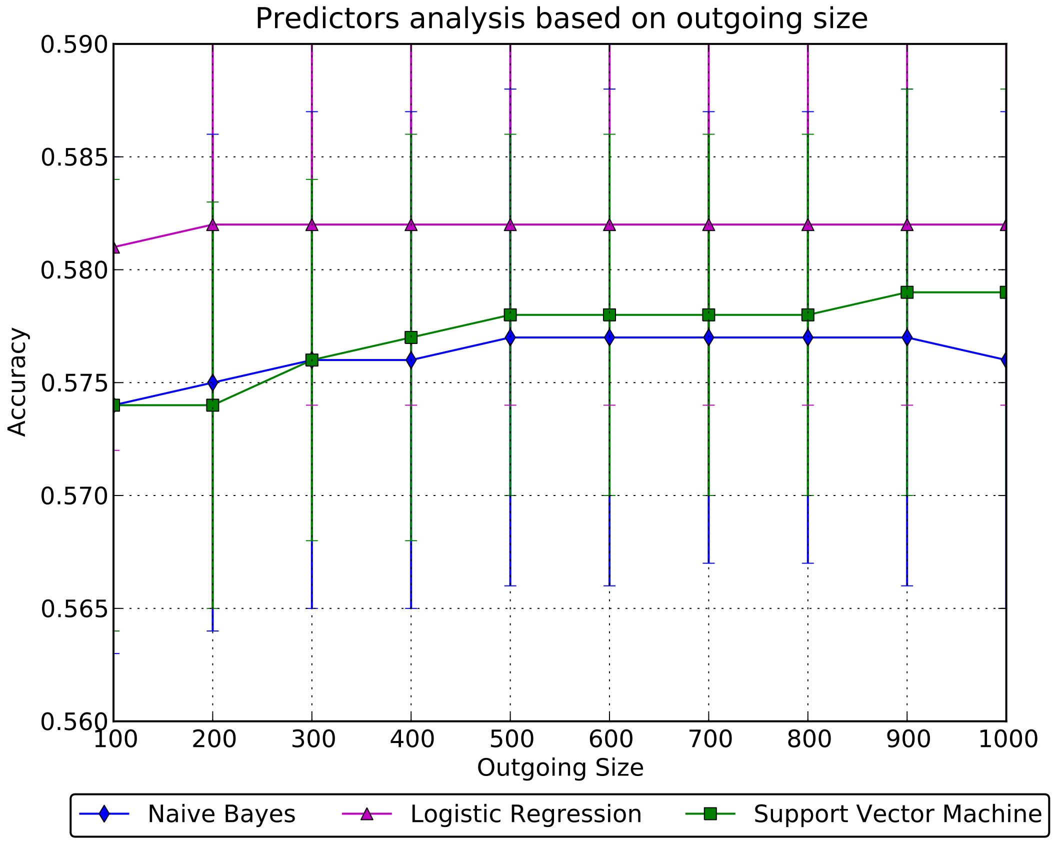


Figure 3.3: Accuracy results for different *outgoing words* sizes. Best performance can be found using LR with a small word size of only 200.

The most predictive *Outgoing Words* words sizes j for each of our classifiers are:

- **Naive Bayes**: 500

- **Logistic Regression**: 200
- **Support Vector Machine**: 900

Using the most predictive word sizes j for each of our classifiers and building our feature vector as defined above we compare to our baselines and obtain:

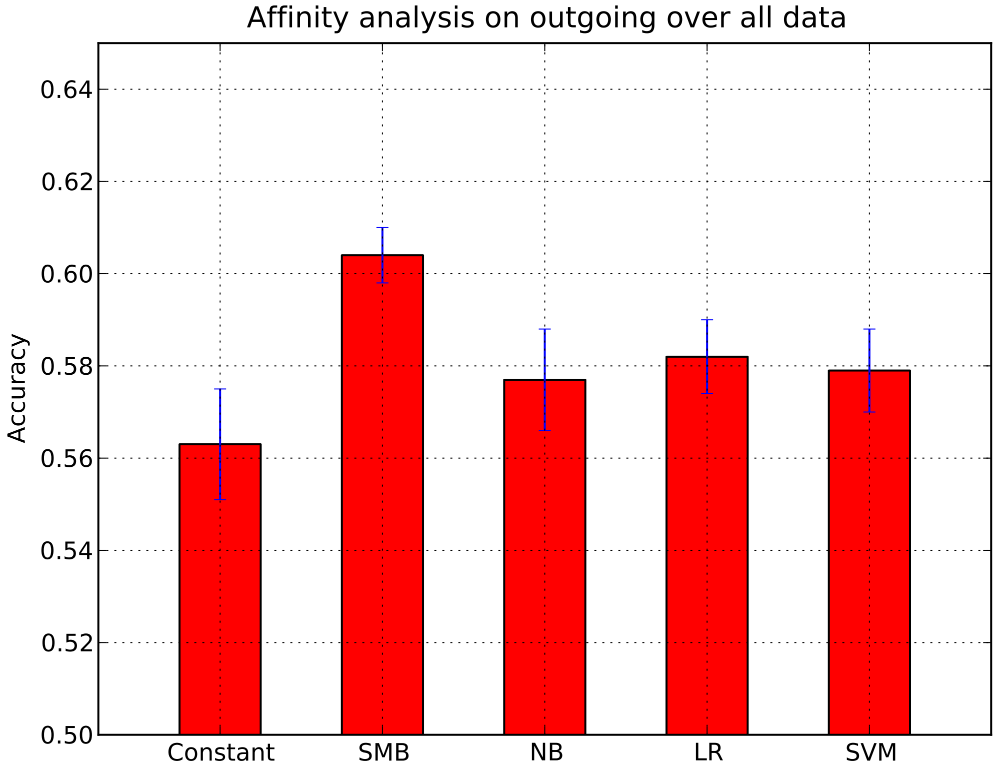


Figure 3.4: Accuracy results using the *outgoing words* features. *Outgoing words* are a weaker predictor then *user interactions*.

These results do not show an improvement over our baselines and in fact are only a marginal improvement over the *Constant* baseline. A possible reason for this could be due to the commonality of the words being tested. Highly common and frequently used words would result in poor predictive tendencies, this is eluded to in our graph above which shows an improvement in predictiveness over step sizes for SVM.

Comparing *Outgoing Messages* against our exposure curve we obtain:

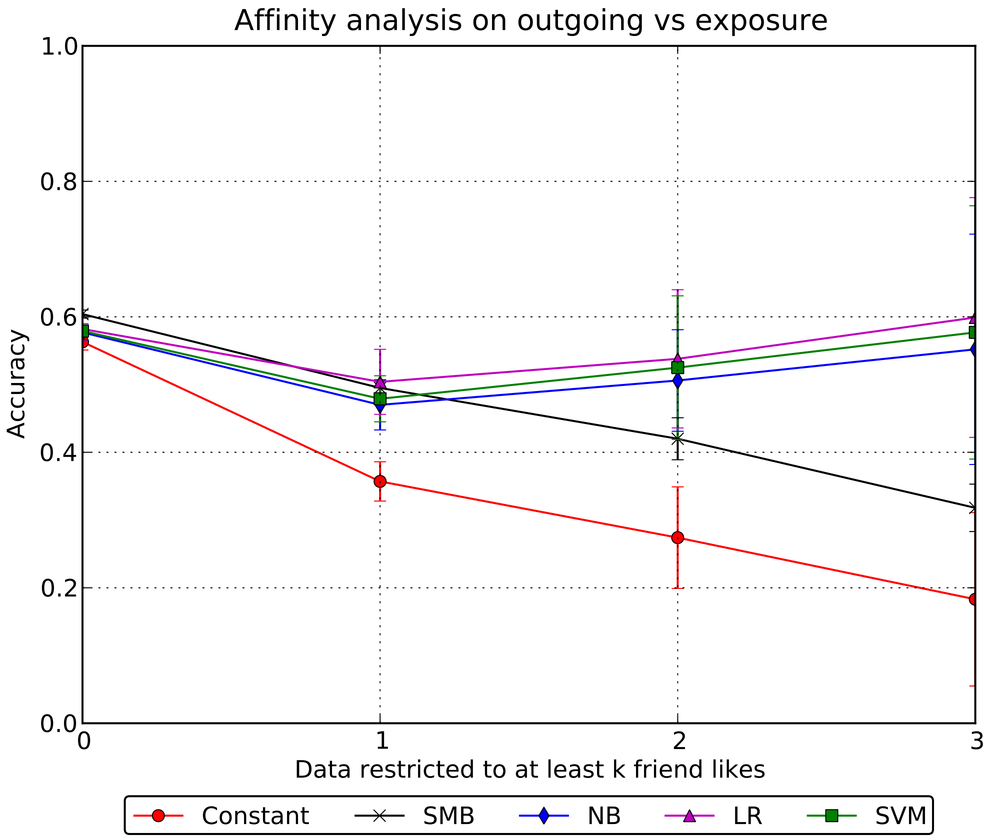


Figure 3.5: Accuracy results against exposure using the *outgoing words* feature vector. *Outgoing words* accuracy improve as k increases, but are less predictive then *user interactions*.

Our exposure curve follows this similar trend of unimproved results for $k = 1$ likes, however as k increases there is some improvement from the baselines, but this is negligible in comparison to $k = 0$ for our classifiers.

3.2.2 Incoming

Similarly for *Incoming Words* we need to discover which is the most predictive j for use of by our classifiers, using the same methodology as described above for *Outgoing Words* we obtain the following graph:

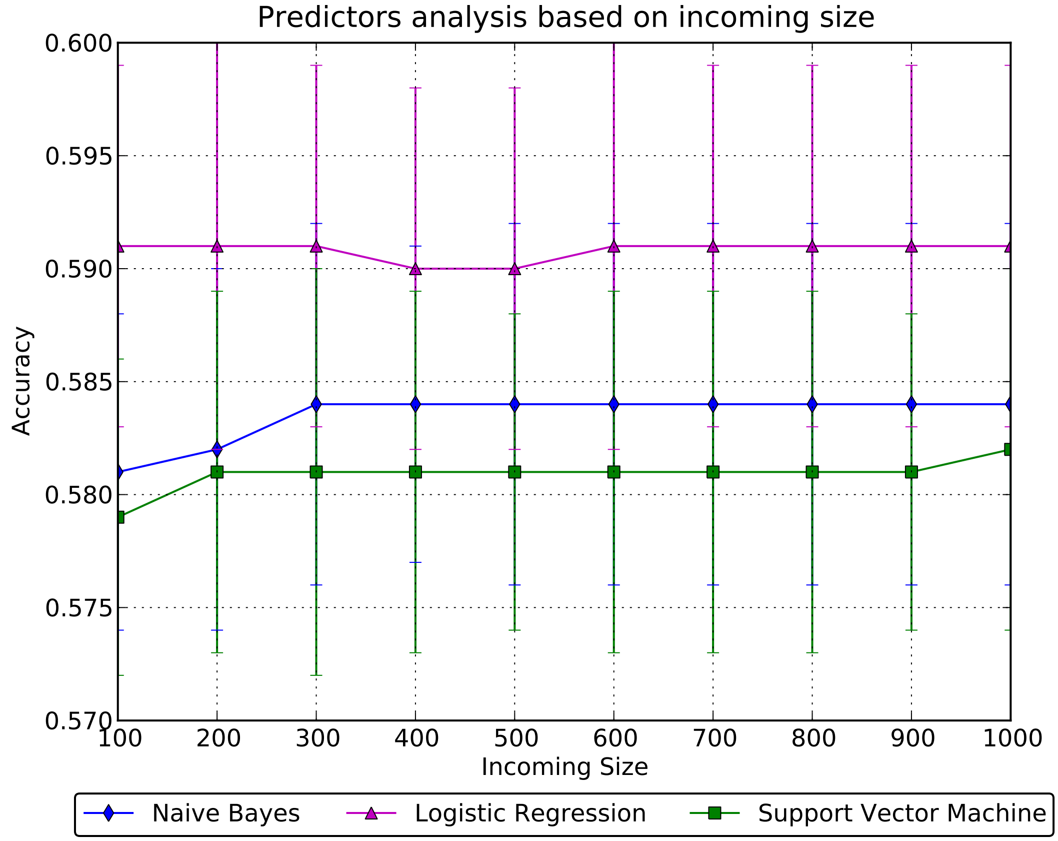


Figure 3.6: Accuracy results for different *incoming words* sizes. *Incoming words* are more predictive then *outgoing words*.

The most predictive *Incoming Words* words sizes j for each of our classifiers are:

- **Naive Bayes**: 300
- **Logistic Regression**: 100
- **Support Vector Machine**: 1000

Using the most predictive word sizes j for each of our classifiers as defined above and comparing to our baselines we obtain:

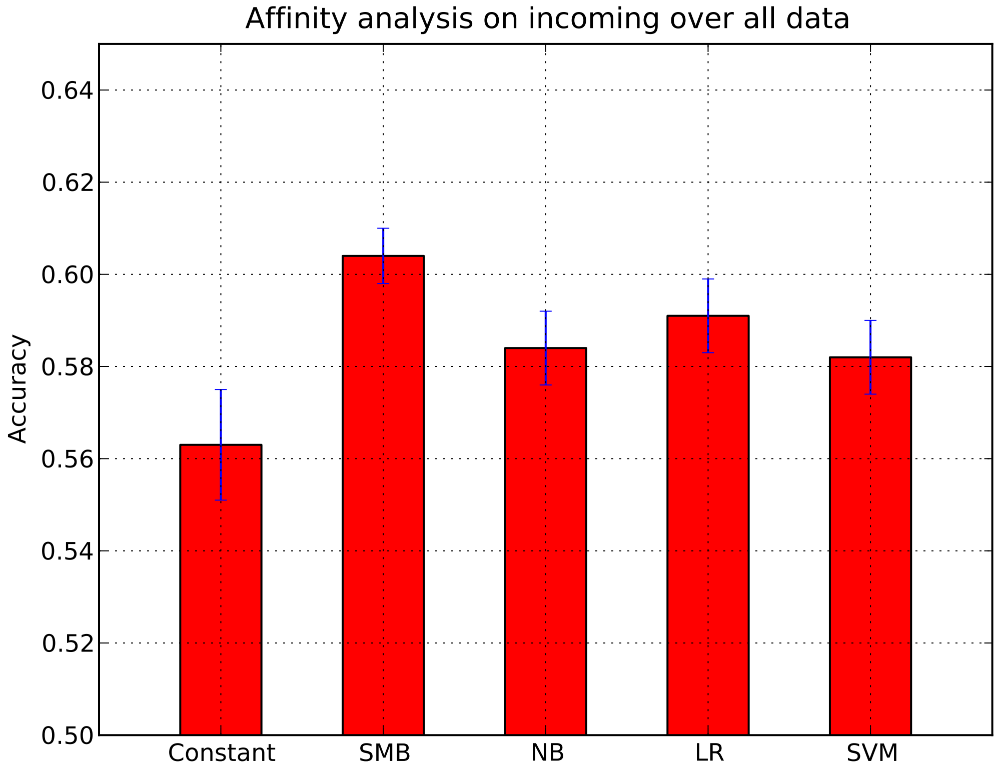


Figure 3.7: Accuracy results using the *incoming words* features. *Incoming words* are a weaker predictor then *user interactions*.

Again, *Incoming Words* themselves are not predictive in comparison to our baselines, however not to the same negative extent as *Outgoing Words*.

Comparing *Incoming Messages* against our exposure curve we obtain:

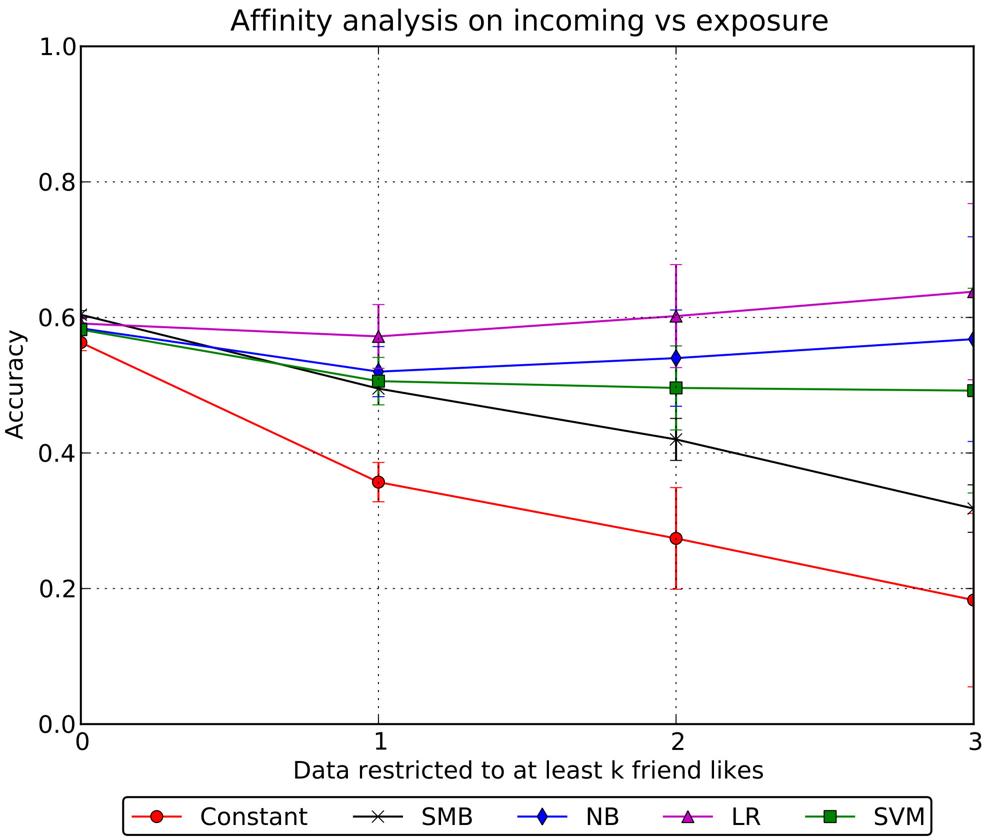


Figure 3.8: Accuracy results against exposure using *incoming words* features. *Imcoming words* accuracy improve as *k* increases, but are less predictive then *user interactions*.

For *user interactions* outgoing are more important, however for *words*, *incoming* are more important.

Similarly, *Incoming Words* improve upon our baselines as *k* increases, however this performance increase is negligible in comparison with $k = 0$ and hence *Incoming Words* do not prove to be predictive of user likes.

3.3 Conclusion

Throughout this section we have explored different avenues available for users to maintain interactions between other users.

We have found that words, irrespective of their directionality do not assist in improving predictions. [Anderson et al. 2012] concluded that it is less important what users say, then who they interact with, which we also found in our results, our interactions results were comparable to our baselines over $k = 0$ and this improvement continued over the exposure curve as our *k* increased.

Our results have shown, that for *User Interactions* it is enough for some user to have previously liked an item, which allows our classification methodology to offer an increase in predictiveness as *k* increases.

Chapter 4

User Preferences

demographics gender and age are predictive

In this section we will discuss the effects of applying different types of *User Preferences* as the feature vector and their predictive tendencies within our data set.

4.1 Demographics

The *Demographics* data we are interested in includes:

- **Age**
- **Birthday**
- **Locale**

Below we will give a basic analysis of the *Demographics* data when extracted from our data set.

Gender breakdown:

Male	**Female**	**Undisclosed**
85	33	1

Table 4.1: Gender breakdown for users.

Despite this clear male bias [Ugander and Marlow 2011] found that in a social setting, there are no strong gender homophily tendencies. Hence the male skew should not negatively affect our results. Additionally [Backstrom et al. 2011] have shown that different genders have differing tendencies to disperse interactions across genders, implying our male skew should be unimportant. Hence gender information will be used in the *Demographics* feature vector.

Birthday breakdown:

Year	**Frequency**
Undisclosed	1
1901-1905	1
1906-1910	0
1911-1915	1
1916-1920	0
1921-1925	0
1926-1930	0
1931-1935	0
1936-1940	1
1941-1945	0
1946-1950	0
1951-1955	0
1956-1960	2
1961-1965	1
1966-1970	4
1971-1975	10
1976-1980	12
1981-1985	25
1986-1990	34
1991-1995	25
1996-2000	2

Table 4.2: Birthday breakdown

Birthdays are grouped in a distinct range, most users in this data set are grouped in the age ranges of $\{18 - 30\}$. [Ugander and Marlow 2011] have found that there is a strong effect of age on friendship preferences. Hence birthday information will be used in this feature vector.

Location breakdown:

Location	**Frequency**
Undisclosed	33
Ahmedabad, India	1
Bangi, Malaysia	1
Bathurst, New South Wales	1
Bellevue, Washington	1
Braddon, Australian Capital Territory, Australia	1
Brisbane, Queensland, Australia	2
Canberra, Australian Capital Territory	56
Culver City, California	1
Frederick, Maryland	3
Geelong, Victoria	1

Table 4.3: Location breakdown

Given the fact that most users are either situated in the ACT (location of the app development and deployment) or are undisclosed, location information will not be used for this feature vector.

For *Demographics* the I of our feature vector X is defined by the following conditions:

- Whether the user is male.
- Whether the user is female.
- Whether the user and any user in the alters set share the same gender.
- Whether the user and any user in the alters are of a different gender.
- Whether the user and any user in the alters set share the same birth range.

Denote the set of $G \in \{m, f\}$
$u = male$ $u = female$ $u = male \wedge$
$u = male \wedge \exists male \in \{alters\}$

The alters of I can then be defined as the set of users who have liked the current item M. Each component of I is set to 1 if any of the alters have meet the conditions described above, in comparison (where required) with the user n, otherwise it is set to 0.

Applying this feature vector to our classifiers we obtain:

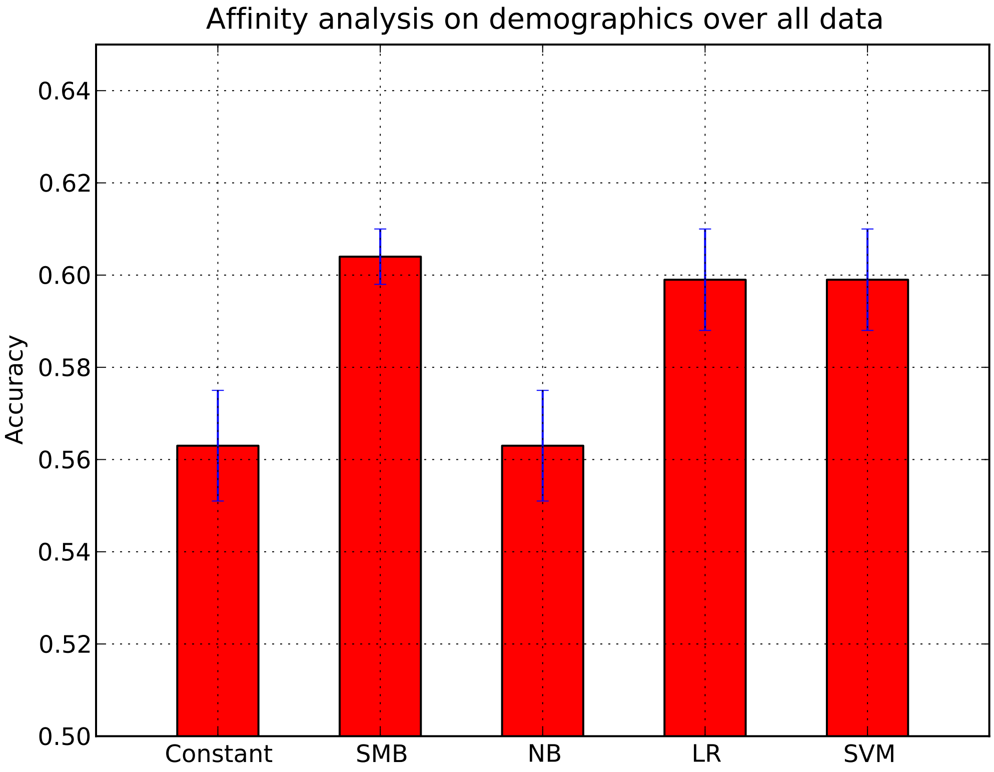


Figure 4.1: Accuracy results using the *Demographics* feature vector.

The *Demographics* feature vector shows our first positive results, this feature vector almost performs as well as our SMB baseline for the case of $k = 0$.

Comparing *Demographics* against our exposure curve we obtain:

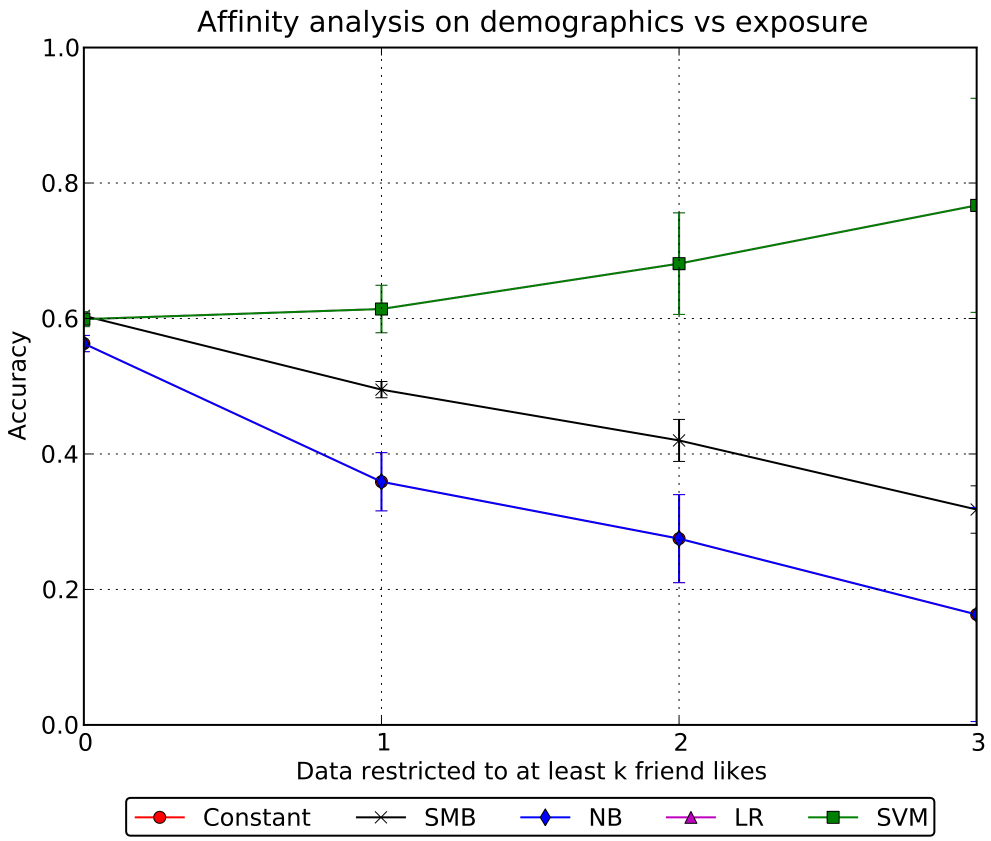


Figure 4.2: Accuracy results for an exposure curve using the *Demographics* feature vector. Note in this case Constant = NB and LR = SVM.

The exposure curve for *Demographics* shows a sizable improvement over our baselines as our *k* increases. This demonstrates that as the number of friends who like an item increases, the probability that a user will like that item also increases. This positive corelation between number of likes and user likes increases with each *k*.

4.2 Traits

Facebook facilitates a wide variety of user chosen preferences which we have defined as *Traits*. These *Traits* allow users to define under a specific area of their profile different areas or activities they are interested in or associate with.

User *Traits* we will investigate include:

- Activities
- Books

- Athletes
- Teams
- Inspirational People
- Interests
- Movies
- Music
- Sports
- Television

Below we display graphs for the different *Traits* sets extracted from our data set. Followed by a subsequent analysis. Each table shows only the frequency of app users for each of the *Traits*.

The *Traits* graphed above can be broken down into three distinct sets based on their locality within the app user base.

- **High Locality**: *Music, Movies, Television* - Showing our app users appear to share similar *Traits* in a media setting.
- **Medium Locality**: *Activities, Books, Interests, Sports* - Showing our app users share some degree of similar preferences across these *Traits*.
- **Low Locality**: *Inspirational People, Athletes, Teams* - Showing our app users do not share many similar preferences across these *Traits*.

For each *Traits* group the I of our feature vector X is defined by the following conditions:

- $I \in \{Activities, Books, Athletes, Teams, InspirationalPeople, Interests, Music, Movies, Sports, Television\}$.

The alters of I can then be defined as the set of users who have liked the current item M. Each component of I is set to 1 if any of the alters have meet the conditions described above for each t, in comparison with the user n, otherwise it is set to 0.

Applying this feature vector to our classifiers we obtain:

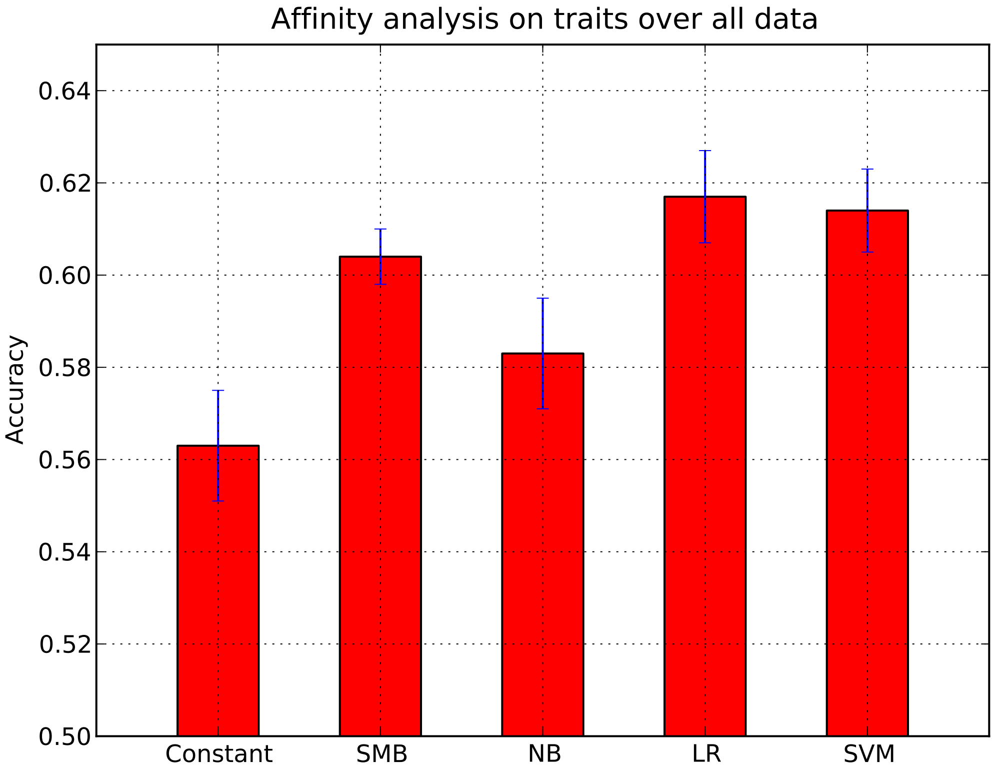


Figure 4.3: Accuracy results using the *Traits* feature vector.

The *Traits* feature vector shows our first improvement over our SMB baseline in the LR and SVM case for $k = 0$ demonstrating that *Traits* are more predictive then user likes for any previously applied method.

Comparing *Traits* against our exposure curve we obtain:

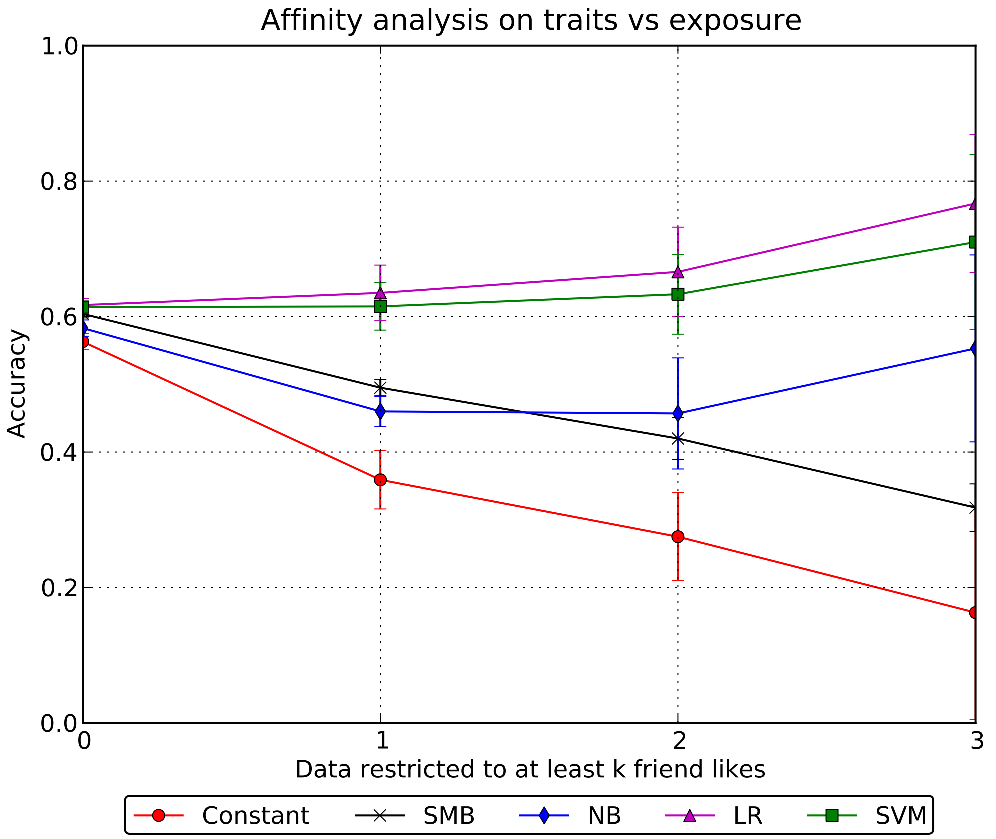


Figure 4.4: Accuracy results for an exposure curve using the *Traits* feature vector.

This trend continues across the exposure curve where each successive increase of *k* causes the performance of our classifiers to increase.

By extracting the model weights from the case where $k = 0$ we can see which *Traits* contain the most predictive qualities:

Trait	**Weight**	**Frequency**
Activities	-5.927 ± 0.001	281
Television	-5.210 ± 0.0	1,029
Music	-3.409 ± 0.001	629
Movies	-2.668 ± 0.001	454
Interests	-1.921 ± 0.001	64
Sports	-1.820 ± 0.001	27
Books	-1.769 ± 0.0	163

Table 4.4: *Logistic Regression* feature weights extracted for the case where $k = 0$. The *Trait* column shows which *Trait* is being displayed. The *Weight* column shows the weighting given for this *Trait*. The *Yes'* column displays the number of times this feature vector was set to 1 for a user and the *Distinct* column displays the number of unique times the feature vector was set to 1.

This shows us that *Traits* which exhibit a medium to high degree of locality have a larger influence during classification. [Brandtzg and Nov 2011] found that virtual interactions help reveal common interests, while real world interactions helps to support friendships. These common interests investigated above are clearly predictive of user likes.

4.3 Groups

Facebook facilitates users to join *Groups* for a large and varied set of different types ranging from local sports teams and political preferences to computer games.

The most popular groups for our app users are shown below:

Group Name	**Frequency**
27	ANU StalkerSpace
20	Facebook Developers
15	ANU CSSA
14	CSSA
13	Australian National University
11	ANU - ML and AI Stanford Course
10	iDiscount ANU
10	Our Hero: Clem Baker-Finch
9	Students In Canberra
7	I grew up in Australia in the 90s
7	Grow up Australia - R18+ Rating for Computer Games
7	ANU Engineering Students' Association (ANUESA) 2010
7	ANU Postgraduate and Research Student Association (PARSA)
6	No, I Don't Care If I Die At 12AM, I Refuse To Pass On Your Chain Letter.
6	No Australian Internet Censorship
6	The Chaser Appreciation Society
6	Feed a Child with a Click
6	ANU Mathematics Society
6	ANU International Student Services, CRICOS Provider Number 00120C
6	2011 New & Returning Burton & Garran Hall
5	If You Can't Differentiate Between "Your" and "You're" You Deserve To Die
5	Keep the ANU Supermarket!!!
5	If 1m people join, girlfriend will let me turn our house into a pirate ship
5	The Great Australian Internet Blackout
5	When I was your age, Pluto was a planet.

Table 4.5: App users popular *Groups* breakdown.

In comparison with *Traits*, *Groups* show a higher locality among the most popular groups.

Given the quantity of groups on Facebook, we need to find some optimal test size j for our data set. Given memory and time constraints we tested within a range of $\{100 - 1000\}$ with an incremental step size of 100 for each test.

The results for these tests are shown below:

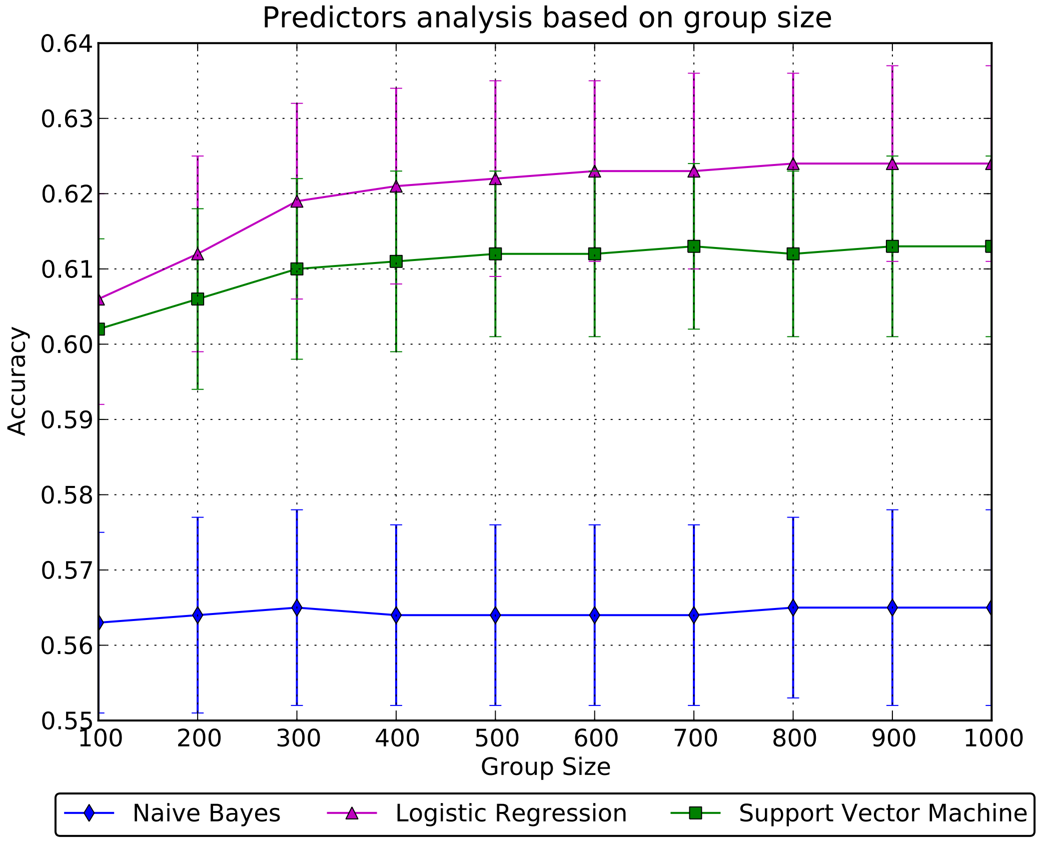


Figure 4.5: Accuracy results for different *Groups* sizes

More gruops help. Localitly.
The most predictive *Group* sizes *j* for each of our classifiers are:

- **Naive Bayes**: 300
- **Logistic Regression**: 900
- **Support Vector Machine**: 800

LR and SVM show a gradual increase as this group size increases, alluding to the possibility of an even higher group size being optimal.

For *Groups* the I of our feature vector X contains an element i for each of the top j groups sizes defined above.

The alters of I can then be defined as all users who have liked the current item M. Each component of I is set to 1 if any of the alters are a member of the current group j where $i = j$ along with the current user n, otherwise it is set to 0.

Using the most predictive *Group* sizes j for each of our classifiers as defined above and comparing to our baselines we obtain:

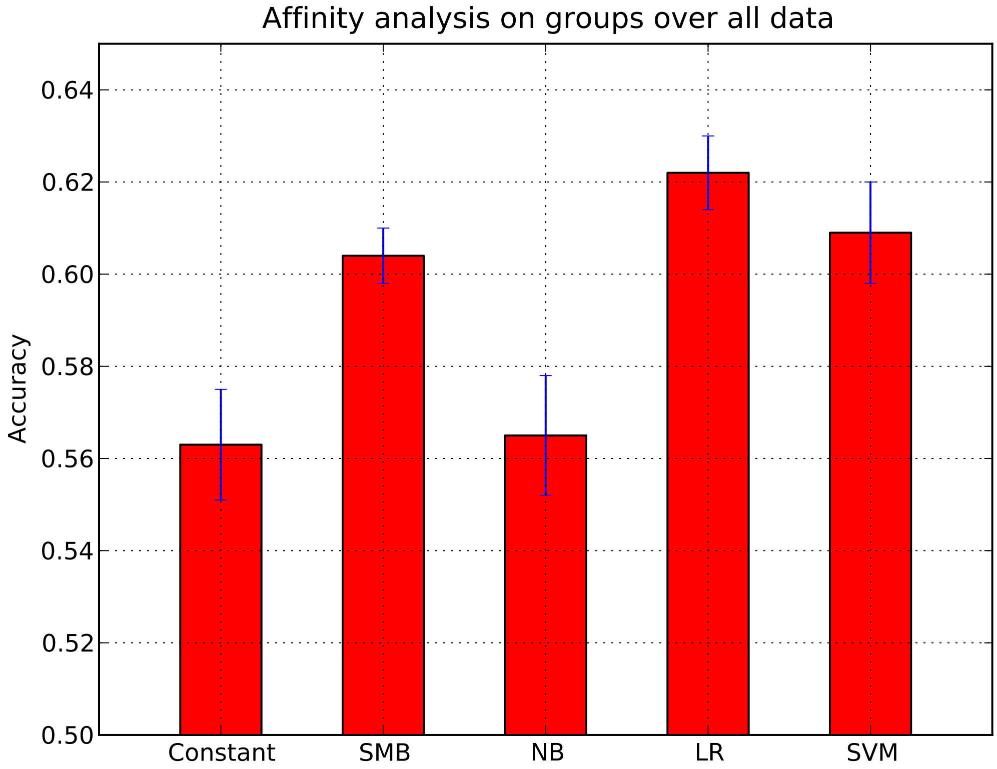


Figure 4.6: Accuracy results using the *Groups* feature vector.

Both LR and SVM show an improvement over our SMB baseline for the case of $k = 0$ demonstrating that *Groups* are more predictive then previous methods.

Applying the *Groups* feature vector across our exposure curve, we obtain:

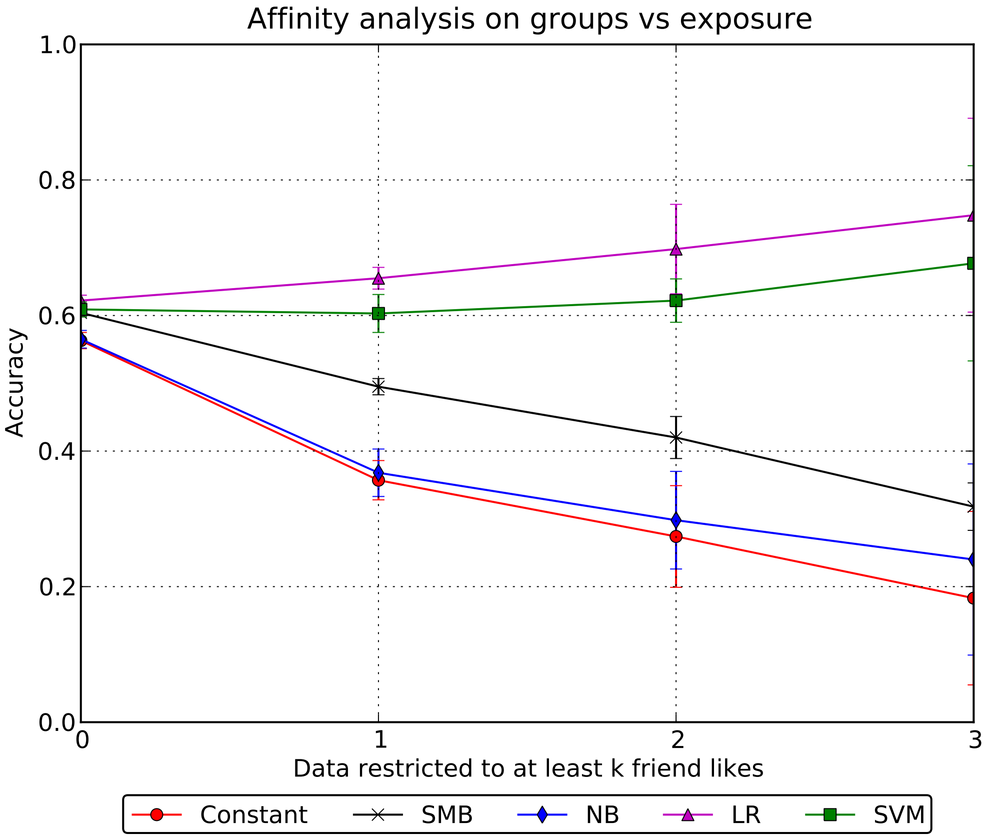


Figure 4.7: Accuracy results for an exposure curve using the *Groups* feature vector.

This trend continues across the exposure curve where each successive increase of *k* causes the performance of our LR and SVM classifiers to increase.

By extracting the model weights from the case where $k = 0$ we can see which *Groups* contain the most predictive qualities:

Name	**Size**	**Weight**	**Frequency**
ANU StalkerSpace	1292	-7.236 ± 0	453
Facebook Developers	487	-3.442 ± 0	177
ANU CSSA	38	-2.742 ± 0	191
Australian National University	619	-2.565 ± 0	70
Overheard at the Ateneo de Manila University	253	-2.462 ± 0	26
iDiscount ANU	338	-2.203 ± 0	88
PETITION FOR FACEBOOK TO INSTALL A DISLIKE BUTTON	683	-2.018 ± 0	92
I grew up in Australia in the 90s	731	-1.991 ± 0	75
Grow up Australia - R18+ Rating for Computer Games	222	-1.951 ± 0	102
Heavy Metal - CANBERRA METAL	30	-1.694 ± 0	42

Table 4.6: *Logistic Regression* feature weights extracted for the case where $k = 0$. The *Name* column displays the name of the feature vector. *Size* represents the size of the *Page* or *Group*. *Weight* represents the weight this feature vector received. *Yes'* column displays the number of times this feature vector was set to 1 for a user. *Distinct* column displays the number of unique times the feature vector was set to 1.

Groups of a relatively small size, but a relatively high concentration of app users appear to be most predictive of user preferences.

4.4 Pages

Facebook facilitates users to like *Pages* for 'things' they like across a large and varied set of different areas ranging from web browsers and TV shows to schools.

The most popular *Pages* liked by our app users are shown below:

Page Name	**Frequency**
33	ANU Computer Science Students' Association (ANU CSSA) 2011
32	The Australian National University
31	ANU Stalkerspace
21	Humans vs Zombies @ ANU
20	The Big Bang Theory
19	Australian National University
19	How I Met Your Mother
18	ANU LinkR
18	ANU ducks
17	Australian National University Students' Association
16	Google
15	Google Chrome
15	ANU XSA
15	Facebook
14	YouTube
14	The Simpsons
13	Portal
13	Top Gear
13	Music
13	ANU Memes
12	Futurama
12	Scrubs
12	ANU O-Week 2012: Escape to the East
12	The Stig
11	Black Books

Table 4.7: App users *Pages* breakdown.

In comparison with *Traits* and *Groups*, *Pages* show a higher locality across the most popular pages for app users.

Given the quantity of *Pages* on Facebook, we need to find some optimal test size j for our data set. Given memory and time constraints we tested within a range of $\{100 - 1000\}$ with an incremental step size of 100 for each test.

The results for these tests are shown below:

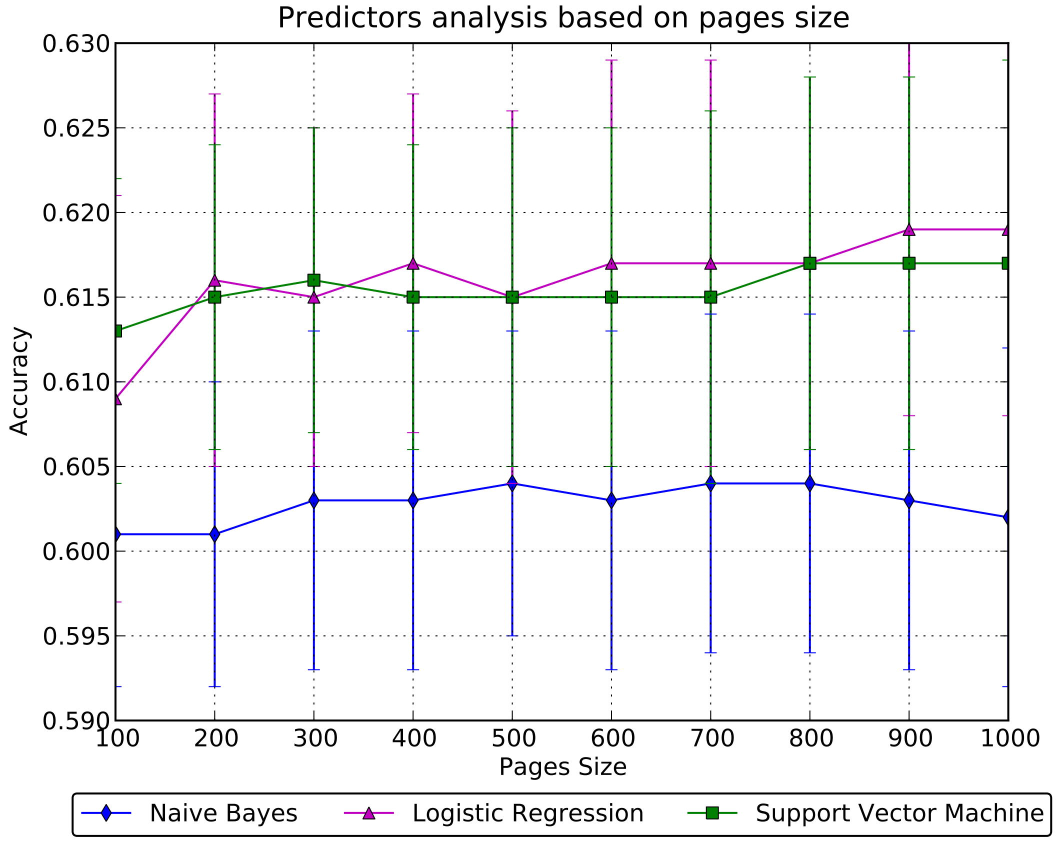


Figure 4.8: Accuracy results for different *Pages* sizes.

The most predictive *Page* sizes j for each of our classifiers are:

- Naive Bayes: 500
- Logistic Regression: 900
- Support Vector Machine: 800

LR and SVM show a gradual increase as this group size increases, alluding to the possibility of an even higher page size being optimal.

For *Pages* the I of our feature vector X contains an element i for each of the top j page sizes defined above.

The alters of I can then be defined as all users who have liked the current item M. Each component of I is set to 1 if any of the alters are a member of the current page j where $i = j$ along with the current user n, otherwise it is set to 0.

Using the most predictive *Page* sizes j for each of our classifiers as defined above and comparing to our baselines we obtain:

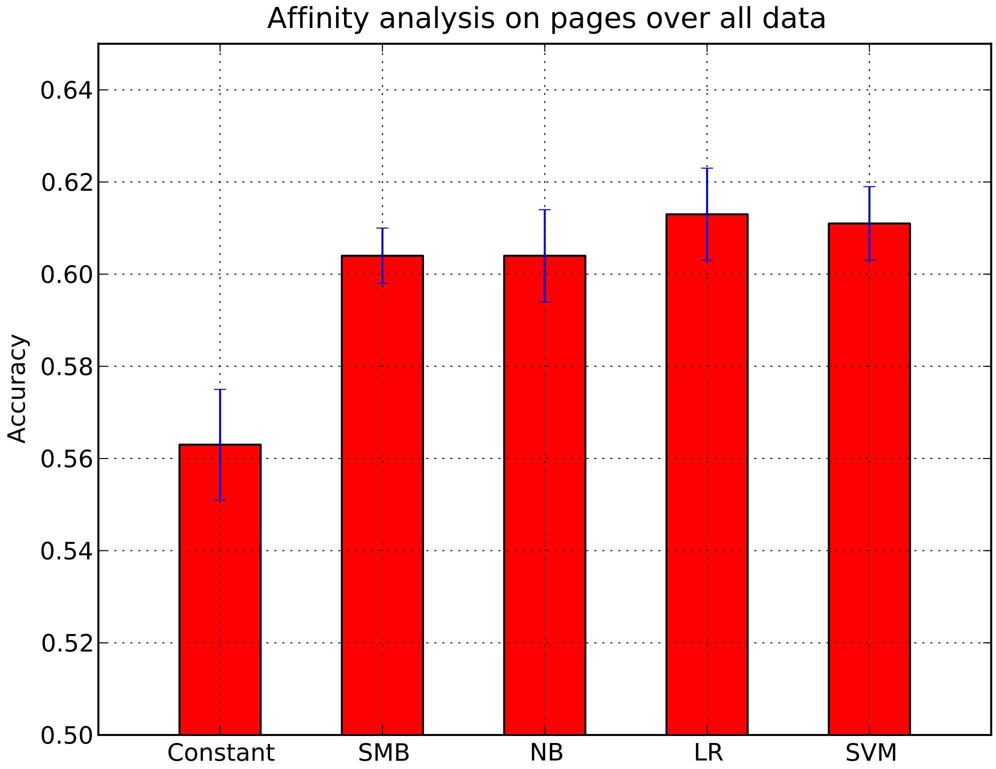


Figure 4.9: Accuracy results using the *Pages* feature vector.

Improvement over SMB, but not groups. Perhaps because more local.

Both NB, LR and SVM show an improvement over our SMB baseline for the case of $k = 0$ demonstrating that *Pages* are also more predictive then previous methods.

Applying the *Pages* feature vector across our exposure curve, we obtain:

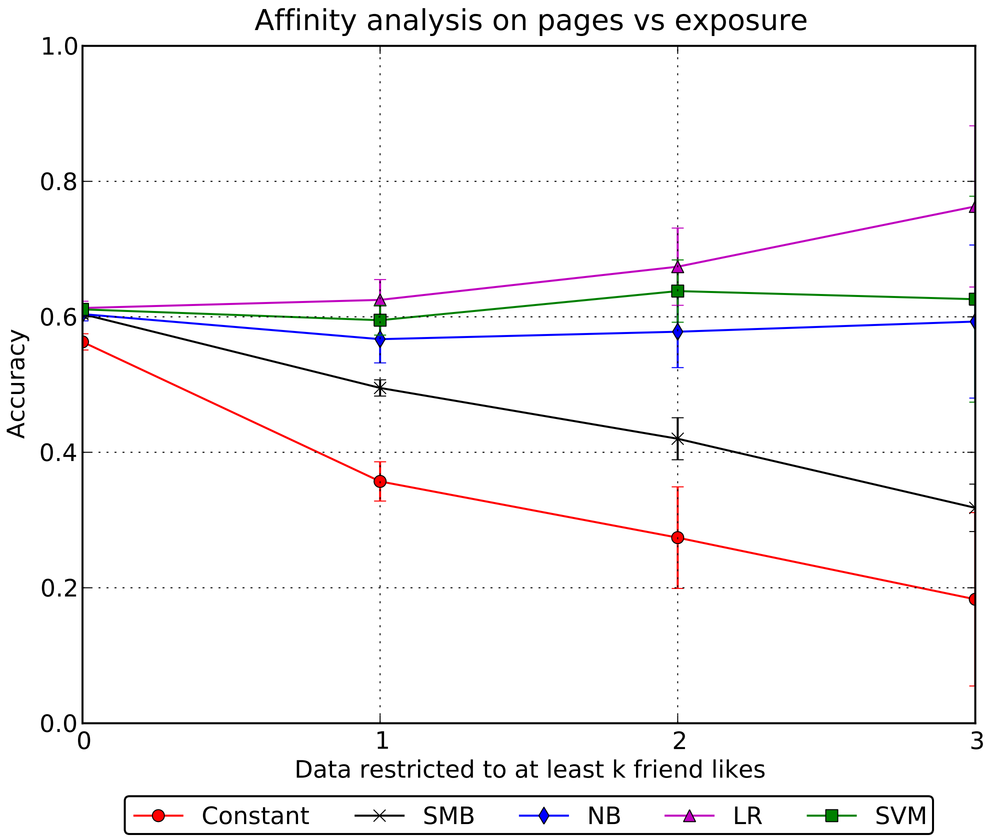


Figure 4.10: Accuracy results for an exposure curve using the *Pages* feature vector.

This trend continues across the exposure curve where each successive increase of *k* causes the performance of our LR and SVM classifiers to increase.

By extracting the model weights from the case where $k = 0$ we can see which *Pages* contain the most predictive qualities:

Name	**Size**	**Weight**	**Frequency**
Sorry mate i can't, i've got Quidditch	254	-1.799 ± 0	18
Avatar: The Last Airbender	324	-1.514 ± 0.001	13
National Geographic	662	-1.437 ± 0.001	18
The Simpsons	1552	-1.414 ± 0	170
Sushi	387	-1.33 ± 0.001	9
House	1746	-1.291 ± 0	66
Seinfeld	609	-1.249 ± 0	15
Starbucks	1548	-1.249 ± 0	7
American Dad	540	-1.215 ± 0.001	18
friends don't let friends vote for Tony Abbott	551	-1.206 ± 0.001	19

Table 4.8: *Logistic Regression* negative feature weights extracted for the case where $k = 0$. The *Name* column displays the name of the feature vector. *Size* represents the size of the *Page* or *Group*. *Weight* represents the weight this feature vector received. *Yes'* column displays the number of times this feature vector was set to 1 for a user. *Distinct* column displays the number of unique times the feature vector was set to 1.

Name	**Size**	**Weight**	**Frequency**
CatDog	259	1.815 ± 0.001	12
Worst. Idea. Ever. [pause] Let's do it.	227	1.737 ± 0	21
Grug	279	1.698 ± 0	9
Kings Of Leon	840	1.607 ± 0.001	14
Planking Australia	166	1.598 ± 0.001	4
Dr. House	964	1.588 ± 0	28
Suit Up	466	1.389 ± 0.001	17
Don't you hate it when Gandalf marks your exam and [..]	110	1.372 ± 0.001	19
Paramore	1004	1.343 ± 0.001	31
Tintin	250	1.339 ± 0.001	11

Table 4.9: *Logistic Regression* feature weights extracted for the case where $k = 0$. The *Name* column displays the name of the feature vector. *Size* represents the size of the *Page* or *Group*. *Weight* represents the weight this feature vector received. *Yes'* column displays the number of times this feature vector was set to 1 for a user. *Distinct* column displays the number of unique times the feature vector was set to 1.

The most predictive *Pages* in our data set are ones which contain a larger number of members and a lower concentration of app users.

4.5 Conclusion

Throughout this section we have explored different avenues available for users to demonstrate their personal preferences across a range of different mediums.

We have found that *User Preferences* are predictive of user likes, particularly for *Traits*, *Groups* and *Pages*. This holds true for the case of $k = 0$ and continues to improve with each successive k.

Similarly as with *User Interactions*, our results have shown, that it is enough for some user to have liked an item to allow our classification methodology to increase in predictiveness.

pages, groups more local. higher prediction of localised likes (local news, events, etc). favourites - high frequency

Chapter 5

Feature Combinations

most predictive features allows for feature selection which is crucial with limited data, cant afford to combing all.

As outlined above, features which positively improved classification were from the *Traits*, *Groups* and *Pages* feature vectors. In this section we combine these positive feature vectors together into a larger feature vector comprised of the individual positively contributing elements.

5.1 Feature Set Selection

given so many features and based on size feature selection is good time consuming and costly

Using the combined feature vector X where I is comprised of:

- *Traits*
- *Groups*
- *Pages*

Applying this feature vector to the data set:

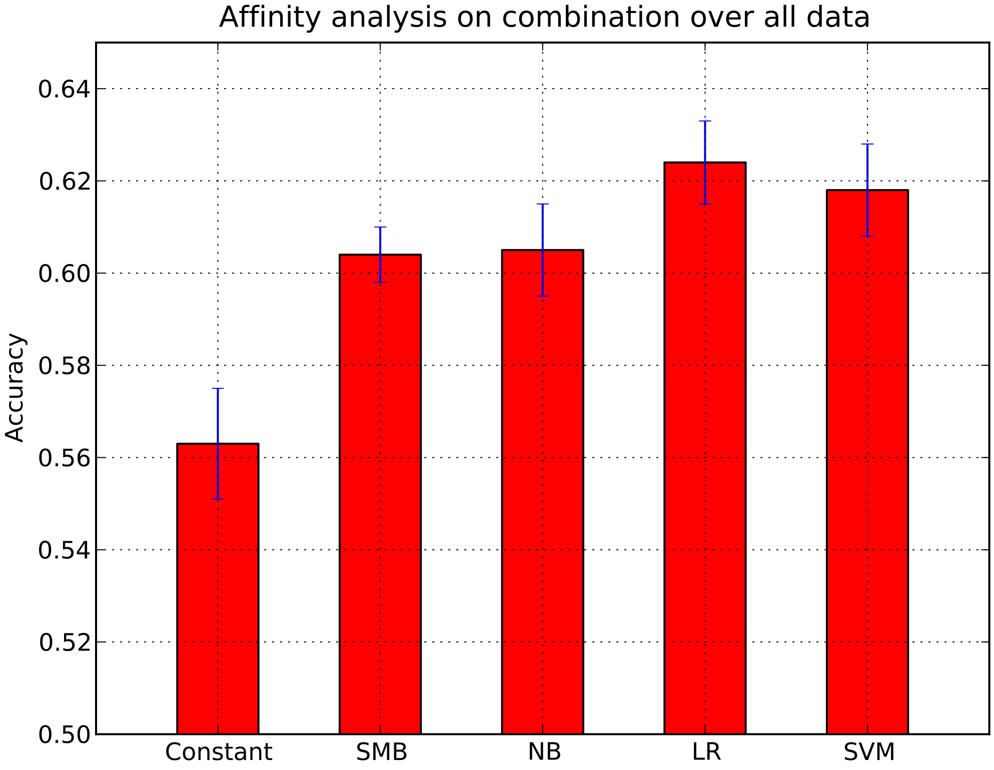


Figure 5.1: Accuracy results using the *Positively Combined* feature set.

We find that the *Combination* feature vector gives better results for our classifiers when compared with our baselines. This holds for all values of k and offers the most predictive feature vector found during this research.

This can be summarised in the table below:

Classifier	**Accuracy**
NB	0.583 ± 0.012
LR	0.617 ± 0.01
SVM	0.614 ± 0.009

Table 5.1: *Traits* results for $k = 0$

Classifier	**Accuracy**
NB	0.604 ± 0.01
LR	0.613 ± 0.01
SVM	0.611 ± 0.008

Table 5.2: *Pages* results for $k = 0$

Classifier	**Accuracy**
NB	0.565 ± 0.013
LR	0.622 ± 0.008
SVM	0.609 ± 0.011

Table 5.3: *Groups* results for $k = 0$

Classifier	**Accuracy**
NB	0.605 ± 0.01
LR	0.624 ± 0.009
SVM	0.618 ± 0.01

Table 5.4: *Combined* results for $k = 0$

These tables show that based on our results the most predictive feature vector is a combination of the individual best feature vectors found in our *User Preferences* section.

too costly to combine all features so need a subset.

Applying this same feature vector across our exposure curve:

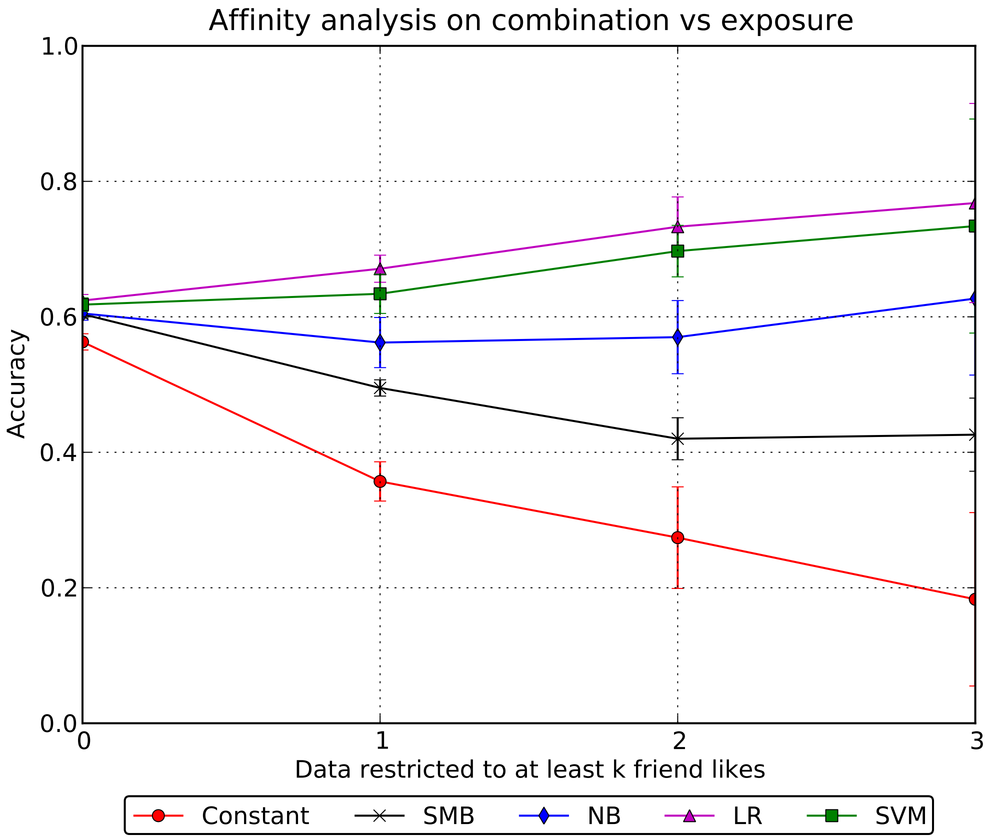


Figure 5.2: Accuracy results for an exposure curve using the *Positively Combined* feature set.

This trend continues over the exposure curve with LR, SVM and NB all improving as *k* increases. Again, this feature vector combination provides the most predictive results when compared with all other analysis completed during this thesis.

By extracting the model weights from the case where $k = 0$ we can see which components of the *Combination* feature vector were most predictive:

Name	**Size**	**Weight**	**Frequency**
Avatar: The Last Airbender (Page)	324	-1.68 ± 0.001	13
I'm late. Got attacked by a wild Pokemon (Page)	161	-1.609 ± 0	20
Overheard at the Ateneo de Manila University (Group)	253	-1.527 ± 0.001	26
Sorry mate i can't, i've got Quidditch (Page)	254	-1.501 ± 0	18
I would.........for Escapium. (Group)	50	-1.467 ± 0.001	11
Burgtoons (Group)	34	-1.37 ± 0.001	7
The Simpsons (Page)	1552	-1.355 ± 0.001	170
City Gate Hall (Group)	27	-1.346 ± 0	5
Victoria's Secret (Page)	764	-1.337 ± 0	11
Starbucks (Page)	1548	-1.313 ± 0	7

Table 5.5: *Logistic Regression* feature weights extracted for the negative case where $k = 0$. The *Name* column displays the name of the feature vector. *Size* represents the size of the *Page* or *Group*. *Weight* represents the weight this feature vector received. *Yes'* column displays the number of times this feature vector was set to 1 for a user. *Distinct* column displays the number of unique times the feature vector was set to 1.

The Negative LR weights are equally broken up into *Pages* and *Groups*, and implies that smaller sizes for both the *Pages* and *Groups* are more predictive, however the number of distinct users who like these *Groups* or *Pages* are quite small.

Name	**Size**	**Weight**	**Distinct**
Don't you hate it when Gandalf marks your exam and [...] (Page)	110	1.627 ± 0.001	19
Goodberry's (Page)	318	1.591 ± 0	73
Worst. Idea. Ever. [pause] Let's do it. (Page)	227	1.561 ± 0	21
CatDog (Page)	259	1.531 ± 0.001	12
Planking Australia (Page)	166	1.501 ± 0.001	4
Avenged Sevenfold (Page)	351	1.471 ± 0	6
Grug (Page)	279	1.465 ± 0	9
Dr. House (Page)	964	1.451 ± 0	28
If 1m people join, girlfriend will let me [...] (Group)	416	1.362 ± 0	68
Do you ride kangaroos? no mate the cool kids ride emus (Page)	321	1.333 ± 0.001	23

Table 5.6: *Logistic Regression* feature weights extracted for the positive case where $k = 0$. The *Name* column displays the name of the feature vector. *Size* represents the size of the *Page* or *Group*. *Weight* represents the weight this feature vector received. *Yes'* column displays the number of times this feature vector was set to 1 for a user. *Distinct* column displays the number of unique times the feature vector was set to 1.

The Positive LR weights are equally broken up into *Pages* and *Groups*, though with a stronger *Page* focus which and again implies that smaller sizes for the *Pages* are more predictive, though the trend follows that the number of distinct users who like these *Pages* are quite small.

Chapter 6

Conclusion

In this chapter we will outline a summary of the work completed during this thesis and outlines a proposal for future work in this area.

method improves with exposure

6.1 Summary

In this thesis we have tested and compared an exhaustive list of different affinity features across varied exposures sizes.

We have shown that *user interaction* affinity features in themselves are not predictive of user likes, however coupled with user exposure, they show a comprehensive improvement over our baselines.

We have also shown the interesting result that *user preference* affinity features are more predictive of user likes when compared with our baselines and this trend continues with user exposure.

To answer the question initially proposed for this thesis: We have shown the affinity features which provide the highest predictiveness of user likes come from *user preferences* and not *user interactions*. The most predictive features found in this analysis are *favourites*, *group memberships* and *page likes*.

Which is the exciting novel insight examined proposed in this thesis.

6.2 Future Work

Proposed future work can be summarised under the following points:

- **Increase size ranges**: Given our maximum test sizes for *groups* and *pages* of 1000 this size could be increased to find the optimal testing range for each of our classifiers.

- **Passive likes**: Given the Facebook model of allowing users to like but not dislike data, explicit dislike data can not be gleaned from Facebook, which is hence why the NICTA sourced active likes data was used for this evaluation. An approach could be developed which can predict whether a user will have seen an item (online timestamps, recent interactions with user) and can infer that if the user did not like the item then they disliked it. This data set could then be applied to the testing methodology undertaken above.

- **Cold start**: Leaving out some subset of users when training our models, but including them during testing to explore their effects on results.

- **General user set**: Such as the study done by [Ugander and Marlow 2011] which comprised of the entire active social network of 721 million users (as of May 2011), applying these methods to a data set which is more indicative of the general Facebook user population could offer more generalisable results.

- **Bayesian Model Averaging**: Weighting the most successful machine learning models under different affinity features and exposures to generate a new combined classifier, which combines the best results of each individual classifier.

Appendix A

Traits

Frequency	Activity
10	Sleeping
5	Eating
5	Reading
4	Running
4	Cycling
4	Minecraft
4	Programming
3	Android
3	Cooking
3	Video Games
3	Xbox 360
3	Piano
3	Guitar
3	Badminton
3	Chocolate

Table A.1: Top *Activities* for app users

Frequency	Inspirational People
2	Alan Turing
1	Bender
1	Maurice Moss
1	Steve Jobs
1	Sean Parker
1	Pope Benedict XVI
1	Martin Luther
1	Alistair McGrath
1	St Augustine
1	Dennis Ritchie
1	Linus Torvalds
1	Richard Stallman
1	C. S. Lewis
1	Mike Oldfield
1	Ryan Giggs

Table A.2: Top *Inspirational People* for app users

Frequency	Book
7	Harry Potter
4	The Bible
3	Harry Potter series
3	Discworld
3	That's 3 minutes of solid study, think I've earned 2hrs of Faceboook time
3	Freakonomics
3	Tomorrow when the War Began
2	Magician
2	Hitchhiker's Guide To The Galaxy
2	The Discworld Series
2	Terry Pratchett
2	Terry Pratchett
2	George Orwell
2	Lord Of The Rings
2	Goosebumps

Table A.3: Top *Books* for app users, here we see an example of the non-distinct properties inherent in Facebook, where books can have the same name, yet still be regarded as a different entity.

Frequency	**Interest**
5	Movies
5	Music
3	Cooking
3	Sports
2	Psychology
2	Internet
2	Video Games
2	Martial arts
2	Literature
2	Economics
2	Tennis
2	Badminton
2	Artificial intelligence
2	Computers
2	Travel

Table A.4: Top *Interests* for app users.

Frequency	**Music**
9	Daft Punk
9	Muse
8	Michael Jackson
8	Pink Floyd
8	Lady Gaga
7	Linkin Park
7	Avril Lavigne
6	Radiohead
6	Rihanna
6	Coldplay
6	Green Day
6	Katy Perry
6	Taylor Swift
5	Gorillaz
5	Queen

Table A.5: Top *Music* for app users.

Frequency	**Movie**
9	Inception
8	Avatar
8	Fight Club
7	The Lord of the Rings Trilogy (Official Page)
6	Star Wars
6	I wouldnt steal a car, But i'd download one if i could
6	WALL-E
6	Scott Pilgrim vs. the World
6	Toy Story
6	Shrek
5	Batman: The Dark Knight
5	Harry Potter
4	The Matrix
4	The Social Network Movie
4	Monsters, Inc.

Table A.6: Top *Movies* for app users.

Frequency	Sport
8	Badminton
5	Basketball
3	Cycling
3	Volleyball
2	Starcraft II
2	Football en salle
2	Swimming
2	Towel Baseball
2	Tennis
1	Soccer
1	Taekwondo
1	Rock climbing
1	In The Groove
1	Darts
1	Table tennis

Table A.7: Top *Sports* for app users.

Frequency	Television Show
20	The Big Bang Theory
19	How I Met Your Mother
14	The Simpsons
13	Top Gear
12	Futurama
12	Scrubs
11	Black Books
10	Black Books
10	South Park
10	Family Guy
9	The Daily Show
8	The IT Crowd
8	FRIENDS (TV Show)
7	True Blood
7	MythBusters

Table A.8: Top *Television* shows for app users.

Frequency	Athlete
4	Roger Federer
4	Rafael Nadal
3	Maria Sharapova
2	Leo Messi
1	Andy Schleck
1	Chrissie Wellington
1	Emma Snowsill
1	Emma Moffatt
1	Barbara Riveros
1	The Brownlee Brothers
1	Marie Slamtoinette #1792
1	Wayne Rooney
1	”you are what you eat” ” I dont remember eating a Tank.”
1	Nemanja Vidic
1	Ryan Giggs

Table A.9: Top *Athletes* for app users.

Frequency	Team
5	Manchester United
2	Bear Grylls cameraman appreciation society
2	Real Madrid C.F.
2	Liverpool FC
1	Leopard Trek
1	British Triathlon
1	TeamCWUK
1	Surly Griffins
1	Canberra Raiders
1	Kolkata Knight Riders
1	Brisbane Roar FC
1	Brisbane Broncos
1	Cricket Australia
1	— Manchester United Fans —
1	Juventus

Table A.10: Top *Teams* for app users.

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