A Social Recommender System For Wines

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Abstract

This is the paper's abstract …

Contents

1 Introduction

Recommender Systems.

Since their origin in the mid-1990s with systems such as Tapestry [6] and GroupLens [9], recommender systems have become ubiquitous on the World Wide Web, being employed by some of the worlds largest online businesses as core parts of their offering.

It is the growth of the Web, which is now ubiquitous itself, that has given companies the ability to draw on unprecedented amounts of data about their users' preferences. At the same time the Web has made it easier than ever to reach their users with tailored suggestions.

Amazon's system of product recommendations using item-to-item collaborative filtering is regarded as a "killer feature"[7], and is one of the defining features of the Amazon brand experience. Amazon state their mission to be, "to delight our customers by allowing them to serendipitously discover great products"[7].

Netflix's movie recommender system *Cinematch* "Netflix Prize" competition

Social Recommender Systems.

In recent years social applications have dominated the Web. Networks like Facebook and Twitter have become massive global businesses as Internet users share more and more of their lives online. In such a context recommender systems are able to look beyond users' relationships to product and services, being able instead to interrogate qualitative data about the relationships between specific people. Facebook describe this as the "social graph".

CITATIONS NEEDED!

These systems, "a class of recommender systems that target the social media domain"[**?**], represent the current state of the art.

Recommending Wines.

Recommender systems for wines are not a new idea, being typical of the kind of item many systems are designed to recommend. Burke developed the VintageExchange FindMe recommender system in 1999[1], and there is at least one patent pending with the WIPO for a wine recommender system[**?**].

As a knowledge-based recommender, Burke's FindMe system, "required approximately one person-month of knowledge engineering effort"[2].

The Tetherless World Wine Agent (TWWA), by Patton and McGuinness[**?**]. The TWWA project is primarily concerned with knowledge representaion and the Semantic Web, presenting a common and collaborative ontology for wine with which users can share wine recommendations across their social networks[11]. The system does not automatically tailor recommendations to users, although this is stated as a target for future work[11].

Service Oriented Architecture.

I have chosen to implement my system as a service, such

Aims and Objectives.

I aim to produce a recommender system for wines which takes advantage of both ratings and tasting notes to suggest the most interesting wines and users. I intend the system to ignore wine attributes, such as grape variety and colour, preferring to make recommendations based on a hybrid of pure collaborative filtering and a content-based filtering approach using user-submitted and expert tasting notes.

Rather than implement a full graphical interface for the system I have chosen to develop an HTTP API.

In doing so I will explore the field of recommender systems,

Why are these systems interesting - Benefits - Challenges

Typical applications... - Movies - Products (i.e. Amazon)

Applications in wine domain - what's the same - what's different

What will this project do? - implement a recommender system for wines - exploration of techniques etc.

2 Literature Review

The term *recommender system* was coined by Resnick and Varian [10] to describe a system that "assists and augments" the "natural social process" of recommendation, with Resnick and Varian stating that they preferred it to the more narrow term "collaborative filtering" used by Goldberg et al. [6] to describe their Tapestry system.

The growth of the World Wide Web has seen recommender systems become a ubiquitous part of everyday life, with companies such as Amazon, Facebook, Twitter and Google using making recommendations to millions of us every day.

. . .

There are several main categories of filtering technique employed in recommender systems. Burke [4] presents five: *collaborative*, *content-based*, *demographic*, *utility-based* and *knowledge-based*. Table 1 details these methods and their characteristics.

Collaborative Filtering.

— off the web (?) — on the web...
– What are the methods employed in recommender systems?
– Collaborative Filtering - User-based filtering - Item-based filtering
– Content-Based Filtering - Variants
– Characteristics of the domain
— Cold start problem — Sparsity problem — ... etc.

Table 1: Recommendation Techniques, reproduced from Burke, 2002 [4]

Technique	Backgroud	Input	Process
Collaborative	Ratings from U of items in I.	Ratings from u of items in I.	Identify users in U similar to u, and extrapolate from their ratings of i.
Content-based	Features of items in I.	u's ratings of items in I.	Generate a classifier that fits u's rating behaviour and use it on i.
Demographic	Demographic information about U and their ratings of items in I.	Demographic information about u.	Identify users that are demographically similar to u, and extrapolate from their ratings of i.
Utility-based	Features of items in I.	A utility function over items in I that describes u's preferences.	Apply the function to the items and determine i's rank.
Knowledge-based	Features of items in I. Knowledge of how these items meet a user's needs.	A description of u's needs or interests.	Infer a match between i and u's need.

3 Development Method

4 The Sommelier System

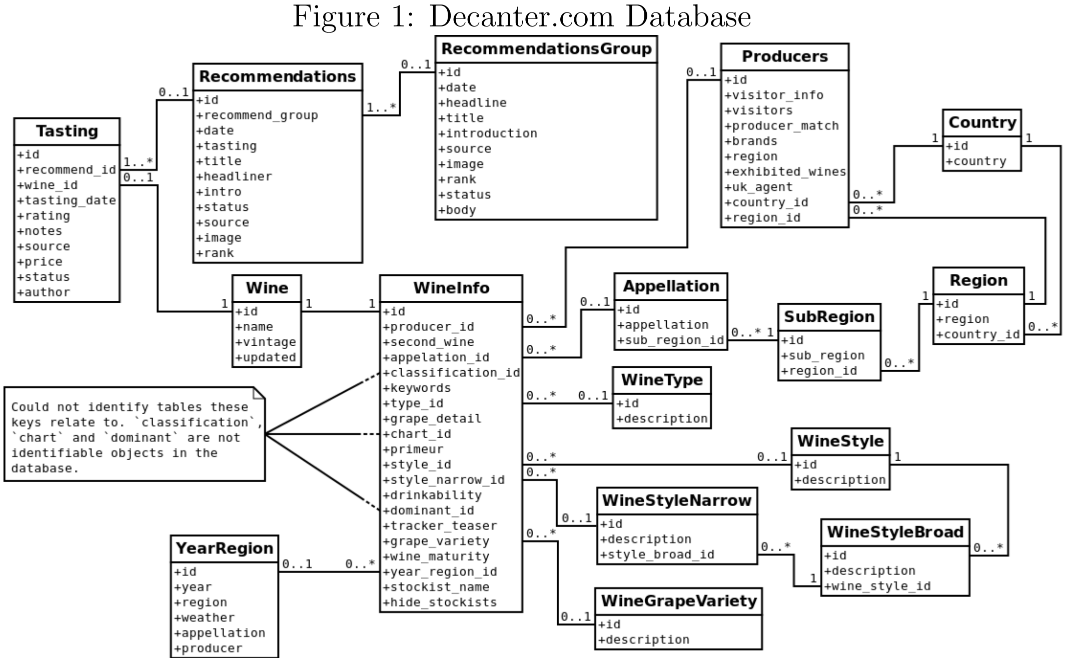
Data Cleanup

The data source I have used for my project is the wines database belonging to Decanter.com[**?**]. The database contains nearly 40,000 professional ratings and tasting notes for wines from as far back as 1986, featuring vintages as far back as 1917.

The original database is highly inconsistent, displaying a mixture of design approaches and a variable quality of data. This is consistent with the fact that the database has been developed over a long period of time by a number of different developers with varying levels of skill, and that wine journalists making entries into the database have taken a number of idiosyncratic approaches to data entry.

Nevertheless I considered there to be a great deal of useful and interesting information in the database, with it to contain usable ratings and/or tastings for over 33,000 wines.

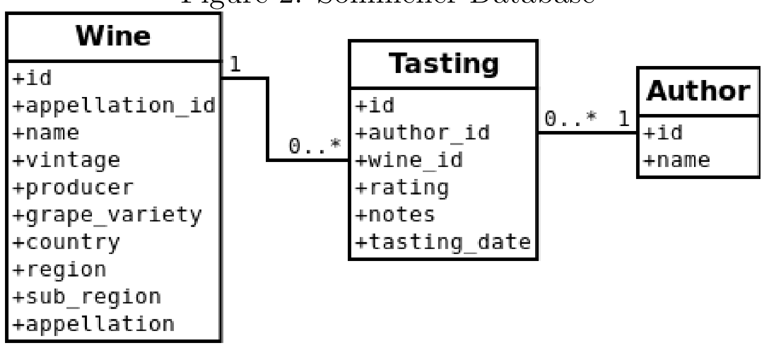
Figure 1: Decanter.com Database



The WineInfo table is a mixture of foreign keys joining to very small tables, such as WineInfo.type_id joining to WineType.id where WineType is a table with only two attributes. This approach, stiving for a high degree of normalisation, contrasts with the fact that the same table also has the attribute second_wine, as a string which only holds data in 450 of the 38762 entries in the table.

Creating The Sommelier Dataset

Figure 2: Sommelier Database



For the new Sommelier database, Figure 2, I decided to denormalise [explanation/citation needed!] the wine data. This enables the data to be queried without joins, maximising the simplicity and execution speed of the queries [citation needed]. Denormalization makes data integrity difficult to maintain however, as there are potentially a large number of records to update for any change in a duplicated value. In this case an appellation or sub-region name changing might require thousands of records to be amended. Creating and editing wines is not a requirement of my system though, so for the purposes of this project the wine and tasting data is static and will not be subject to updates. For this reason the duplication of data within the Wine records is not problematic. In a real world setting this would need to be revisited.

Much of the data from the original database was disregarded entirely.

The tables WineStyleNarrow and WineStyleBroad contained generic text descriptions for wine (“rich and creamy”, “crisp and tangy” etc.). I initially considered this to have potential for migration into tag data which I could reuse as part of my filtering. Unfortunately less than 6435 of the records in WineInfo had non-null values for their style_narrow_id field, and only 3397 of these had corresponding records in the Tasting table. This figure was only around 10% of the number of wines I expected the Sommelier database to contain so I decided that the WineStyle* tables were probably not worthwhile to migrate.

The WineType table was ignored because no wines corresponded to it; no WineInfo.type_id record matched any WineType.id.

The TasterRating and TastingId tables were discarded because they only referenced 1158 of the records in Tasting, too small a proportion of the Tasting table to make it worthwhile migrating them into the dataset.

The Author Problem

The biggest shortcoming of the dataset is that the author of a tasting note is often not recorded. The number of wines with notes and known authors is only 1401, with there being 18 named authors on the system.

Table 2 shows the distribution of tastings amongst authors, only 5 of which have tasted and rated more than 100 wines in the database.

In some cases an author's initials or full name are recorded within the text of a tasting note. I decided that extracting and making use of these was impractical given the time constraints of this project.

DESCRIBE DATA SETS BEFORE AND AFTER

THE SOMMELIER DATASET

Having analysed the dataset and conceived an ideal schema, I needed to decide what the criteria to apply when extracting my new dataset from the source data.

Given that the purpose of the dataset is social recommendations, the first decision I made was to discard any wines without both tasting notes and a rating, whether.

Making Recommendations

In Chapter 2 of Collective Intelligence[**?**], Segaran details basic methods for user- and item-based collaborative filtering. Following the guidelines from this chapter I recreated Segaran's recommendation methods and applied them to my dataset.

TODO Comparison of Segaran and Movielens datasets and Sommelier - why the results no good using straightforward methods?

Table 2: Authors of tasting notes and ratings

Author	Wines tasted	Wines also tasted by another
Amy Wislocki	28	-
Andrew Jefford	105	38
Beverley Blanning MW	13	-
Carolyn Holmes	1	-
Christelle Guibert	119	9
Clive Coates MW	6	-
David Peppercorn	44	-
Gerald D Boyd	7	-
Harriet Waugh	250	23
James Lawther MW	226	21
John Radford	2	-
Josephine Butchart	24	1
Norm Roby	4	-
Rosemary George MW	6	-
Serena Sutcliffe	31	15
Stephen Brook	19	3
Steven Spurrier	497	53

TODO appendix of data

1. select a.name, count(t.id) from author a join tasting t on a.id = t.author_id where 0 ¡ (select count(*) from tasting t2 where t2.winei_id = t .wine_id and t2.author_id ¡¿ 0 and t2.author_id ¡¿ t.author_id) group by a.id; +——————–+—————–+ — name — count(t.id) — +——————– –+—————–+ — Steven Spurrier — 53 — — James Lawther MW — 21 — — Josephine Butchart — 1 — — Stephen Brook — 3 — — Christelle Guibert — 9 — — Serena Sutcliffe — 15 — — Harriet Waugh — 23 — — Andrew Jefford — 38 — +——————–+—————–+

2. select a.name, count(t.id) from author a join tasting t on a.id = t.author_id where 0 ¡ (select count(*) from tasting t2 where t2.wine_id = t.wine_id and t2.author_id = N) group by a.id;

Table 3: Matrix of authors with wines tasted in common

Author	SS	JL	JB	SB	CG	SS	HW	AJ
Steven Spurrier (SS)	-	6	1	1	7	0	15	30
James Lawther MW (JL)	6	-	0	0	0	15	0	0
Josephine Butchart (JB)	1	0	-	0	0	0	0	0
Stephen Brook (SB)	1	0	0	-	0	0	1	1
Christelle Guibert (CG)	7	0	0	0	-	0	1	5
Serena Sutcliffe (SS)	0	15	0	0	0	-	0	0
Harriet Waugh (HW)	15	0	0	1	1	0	-	10
Andrew Jefford (AJ)	30	0	0	1	5	0	10	-

5 Testing and Evaluation

How well does the system work? Details of testing and evaluation of the system...

6 Conclusion

Was the project successful?

7 Review

Review / reflections of the project on a personal level. What has been achieved? What were the problems, and how were they overcome?

Lessons learnt...- Data cleanup very time consuming - Literature vast -¿ plural techniques for recommendation: very difficult to work out what strategy is best for given situation.

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