
Music classification mini project: Instructions

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Abstract

This document contains the instructions for the mini project on classification for the course Statistical Machine Learning, 1RT700. The problem is to classify a set of 100 songs, and predict whether Andreas Svensson would like them or not, with the help from a training data set with 500 songs. You are expected to (i) try some (or all) classification methods from the course and evaluate their performance on the problem, and (ii) make a decision which one to use and ‘put in production’ by uploading your predictions to a website, where your prediction will be evaluated and also compared to the performances of the other student groups. You will document your project by writing a report, which will be reviewed anonymously by your peers. A very well implemented and documented project will earn you a ‘gold star’, which gives bonus points on the exam.

0 Requirements

The project is to be done in groups of 3-4 students. All tasks described in this document have to be done in order to pass the project, and of course *all group members have to take part in the project*.

1 Problem

The problem is to tell which songs, in a dataset of 100 songs, Andreas Svensson is going to like (see Figure 1). The data set consists not of the songs themselves, but of high-level features extracted using the web-API from Spotify¹. These high-level features describe characteristics such as the acousticness, danceability, energy, instrumentalness, valence and tempo of each song.



Figure 1: Andreas Svensson listening to music.

To your help, you are provided a training data set with 500 songs, each of which Andreas has labeled with LIKE or DISLIKE. You are expected to use all the knowledge that you have acquired in the course about classification algorithms, to come up with *one* algorithm that you think is suited for this problem and which you decide to put ‘in production’.

¹<https://developer.spotify.com/web-api/get-audio-features/>

Table 1: Details on the available features (from the Spotify API documentation)

Name	Type	Description
acousticness	float	A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
danceability	float	Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.
duration_ms	int	The duration of the track in milliseconds.
energy	float	Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
instrumentalness	float	Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
key	int	The key the track is in. Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C major/D minor, 2 = D, and so on.
liveness	float	Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.
loudness	float	The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typical range between -60 and 0 db.
mode	string	Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived.
speechiness	float	Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
tempo	float	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
time_signature	int	An estimated overall time signature of a track. The time signature (meter) is a notational convention to specify how many beats are in each bar (or measure).
valence	float	A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

1.1 Data sets

The data set to classify is available as `songs_to_classify.csv`, and the training data is available as `training_data.csv`. The format of the data files is described in `readme.txt`. For details on the extracted features, see Table 1. The data sets are available at <http://www.it.uu.se/edu/course/homepage/sml/project/>.

1.2 Background

The problem of predicting user preferences is a hot research topic both in academia and industry: you have probably seen “you would perhaps also like ...” in online services. Within music, a big player has been the Echo Nest, founded in 2005 as a research spin-off from the MIT Media Lab and later acquired by Spotify. Their focus was methods for automated understanding of music, and in 2011 they released a popular benchmark dataset ‘the million song dataset’ (Bertin-Mahieux et al. 2011) which has become popular in the research community (see, for example, Fu et al. 2011; Oord, Dieleman, and Schrauwen 2013), and has similarities to this project. An overview of the scientific field of music recommendation is found in Kaminskis and Ricci (2012), and some pointers to recent advances can be found in Dieleman (2016) and Jacobson et al. (2016).

2 Technical tasks

2.1 Methods to explore

The course has (so far²) covered the five following ‘families’ of classification methods:

- (i) logistic regression
- (ii) discriminant analysis: LDA, QDA
- (iii) K-nearest neighbor
- (iv) Tree-based methods: classification trees, random forests, bagging
- (v) Boosting

²Deep learning, which will be covered later, is also possible to use for classification. You are of course welcome to explore this as well, in addition to the minimum requirements.

In this project, you decide upon *at least* as many ‘families’ as you are group members, and decide in each ‘family’ *at least* one method to explore. Thus, if you are 4 group members, you explore at least 4 methods from at least 4 different ‘families’.

In addition, you should *also* consider the very simple classifier of always predicting LIKE.

2.2 What to do with each method

For *each* method you decide to explore, you should do the following:

- (a) Implement the method. We suggest that you use R, and you may write your own code or use packages (the material from the problem solving sessions can be useful).
- (b) Tune the method to perform well.
- (c) Evaluate its performance using, e.g., cross validation. Note that each model needs to be evaluated using *only* the labeled data that is available in `training_data.csv`, i.e. for the purpose of model validation and selection you should *not* use the test data from `songs_to_classify.csv`. Exactly how to carry out this evaluation is up to you to decide.

Once you have completed the aforementioned tasks, you should with a good motivation select which method you decide to use ‘in production’. Inspiration for a ‘good motivation’ can for instance be found in Section 4.5 in James et al. (2013). When you have decided which method to try ‘in production’, run it on the test data (for which you do not have the true labels) and submit your results to <http://www.it.uu.se/edu/course/homepage/sml/project/submit/> to see how well it performs. You submit your results as a string like 010011011, where 0 means DISLIKE and 1 means LIKE. The web site also contains a leader board, where you can see how well you are doing in predicting Andreas’ music taste, compared to the other groups.

*To pass the project, you only need to submit your final solution to the homepage **once**!* However, for the sake of a fun competition during the project, we allow each group to submit up to one solution per day (only the latest submission each day will be considered). The leader board will be updated at midnight every night.

3 Documentation

You should summarize your work by writing a report, which will be reviewed by your coursemates as well as the teaching assistants.

3.1 What to include in your report

The report should include the following:

- (1) A brief introduction to the problem
- (2) A concise description of each of the considered methods, and how they are applied to the problem. Even if you used high-level commands, such as `glm()` for logistic regression, you should explain what is ‘under the hood’ of the command! *Please, use your own words. We already know what is written in the book and on Wikipedia, so do not copy-paste from there. Writing concise summaries are for your own learning, and their quality is crucial to obtain a gold star.*
- (3) How the methods were applied to the data (which inputs were used, if the inputs were considered as qualitative or quantitative, how parameters were tuned, etc), including motivations of the choices made.
- (4) Your evaluation of how well each method performs on the problem.
- (5) Which method you decided to use ‘in production’, and your (good) arguments for your choice!
- (6) How well your method performs ‘in production’ (as obtained from <http://www.it.uu.se/edu/course/homepage/sml/project/submit/>).
- (7) Your conclusions.
- (8) Appropriate references.
- (9) All code needed to reproduce your reported findings (in an appendix).

3.2 How to format your report

Your report should be submitted as a PDF-file following the style used for the prestigious machine learning conference Neural Information Processing Systems (NIPS), which also is the style used for this document. In the NIPS format, your report should be *no longer than 6 pages* (not counting the reference list and code appendix). Except for the page limitation, you should follow the NIPS style closely, including its instructions for figures, tables, citations, etc.

The recommended word processor to use is Latex. You can access the Latex files from the conference webpage <https://nips.cc/Conferences/2017/PaperInformation/StyleFiles>. If you prefer not to install a Latex compiler on your computer, you can use online services such as ShareLatex (<https://www.sharelatex.com/>) or Overleaf (<https://www.overleaf.com/>). In your .tex-file, add the lines

```
\makeatletter
\renewcommand{\@noticestring}{}
\makeatother
```

before `begin{document}` to suppress the conference-specific footnote.

If you instead prefer using Microsoft Word, OpenOffice, LibreOffice or similar, you may use the older NIPS style files available at <https://nips.cc/Conferences/2015/PaperInformation/StyleFiles>.

When you submit your report for the first time, you should *not* include your own names in the report (since it will be reviewed anonymously by your colleagues)! This is the default status in the Latex files. If you later submit a revised report you should, however, include your names. In Latex this is achieved by the `final` option, i.e., use `\usepackage[final]{nips_2017}`. In the .docx or .rtf format you have to do the changes manually.

3.3 The title of your report

The title of your report should read "Group SXXX (K members): Mini Project Report", where SXXX is the submission-id you will receive in a separate e-mail from the teaching assistants and K is the number of group members in your group (this information needs to be specified manually since the report is submitted anonymously).

3.4 How to submit your report

You submit your report using the student portal. (PhD students not registered via the student portal submit per e-mail to andreas.svensson@it.uu.se.) All submitted reports will automatically be checked for plagiarism using Urkund (<http://www.urkund.com>).

3.5 Contribution statements

As a separate document (a simple text file is enough), you should clearly state the contributions of each group member, clarifying who contributed to which part, etc.

3.6 Peer review of the reports

Your report will be reviewed by another group. You will also receive the report of another group, which you have to review. As a peer reviewer, you are expected to comment on the following aspects of the report:

- (I) Whether the subset of methods chosen to explore is sufficiently large (methods from at least as many ‘families’ as there is group members, plus the method of always predicting LIKE)
- (II) If all tasks (a-c) from Section 2.2 are made for each method.
- (III) Make an assessment of the technical quality of the proposed solution. Have the considered methods been used in a relevant way to address the problem at hand? Are there any flaws in the reasoning and/or motivations used?
- (IV) The report includes everything required from Section 3.1.
- (V) The quality of the language in the report is satisfactory.

The review process is “double blind”, meaning that both the project report and the review report are anonymous. The review report should be submitted as a simple text file (.txt). Start your review report with the following lines:

Peer review of the report from group SYYY

The review is done by group SXXX

Here, SXXX is your submission-id, and SYYY is the submission-id of the group whose report you have reviewed. There is no strict page limit for the review report, but a guideline is 1/2–1 page in plain text. The review report is also submitted via the student portal.

Of course, you should use a polite and constructive language in your review. (Tip: *think about how you would assess your own report before you submit it!*)

After you have submitted your review of the other report, you will get the review on your report from another group, as well as comments and grades from the teaching assistants.

4 Grading

The **first submission** of the report will be graded with one out of four possible grades:

- Fail, if the deadline is missed or the report is far from meeting the criteria. No revision is possible until next time the course is given.
- Revise, if there are only minor issues. A revised version should be handed in before the revision deadline.
- Pass, if the report fulfills all criteria.
- Pass with gold star, if the report fulfills all criteria, and *in addition* is written such that a thorough understanding of the methods is conveyed and has a technical contribution beyond the minimum requirements. This will earn you **5 bonus points** on the written exam (worth roughly half a grade on the exam). The bonus points are valid for the exam in March and the re-exams in June and August, 2018. After these three opportunities, the bonus points expire.

If applicable, the **second submission** of the report (after revision) will be graded with one out of two possible grades:

- Fail, if the deadline is missed or the revised report still does not meet the criteria. No more revision is possible until next time the course is given.
- Pass, if the report fulfills all criteria.

Please not that sub-standard reports will not be given the chance to be revised, and gold stars are only handed out at the first submission.

5 Tip for getting started

Most background (methods, theory, R commands, etc.) you need to complete the mini project have been/will be covered at lecture 3, 4, 5, 6 and 7 and problem solving sessions 3, 4, 5, 6, 7, 8 and 9. If you choose not to try boosting, you do not need lecture 7 and problem solving session 9, etc. *However, to get started, you only need the material from lecture 3 and 4.*

6 Deadlines & other important dates

Moment	Date
Last chance to submit to http://www.it.uu.se/edu/course/homepage/sml/project/submit/	Thursday February 22
Submission of report	Friday February 23
Receive the report of another group to peer review	Monday February 26
Submit your peer review of another group's report	Thursday March 1
Receive peer review and teaching assistants' comments	Wednesday March 7 (at the latest)
Hand in revised report (if required)	Sunday March 18

All deadlines are one minute before midnight, i.e., 23:59. All tasks in the table above are mandatory in order to pass the project.

Good luck!

References

- Bertin-Mahieux, Thierry, Daniel P.W. Ellis, Brian Whitman, and Paul Lamere (2011). "The million song dataset". In: *Proceedings of the 12th International Society for Music Information Retrieval Conference (ISMIR)*.
- Dieleman, Sander (2016). "Keynote: Deep learning for audio-based music recommendation". In: *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems*.
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- Jacobson, Kurt, Vidhya Murali, Edward Newett, Brian Whitman, and Romain Yon (2016). "Music Personalization at Spotify". In: *Proceedings of the 10th ACM Conference on Recommender Systems*.
- James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani (2013). *An introduction to statistical learning. With applications in R*. Springer.
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- Oord, Aaron van den, Sander Dieleman, and Benjamin Schrauwen (2013). "Deep content-based music recommendation". In: *Advances in Neural Information Processing Systems 26 (NIPS)*.