Selected Papers

Computational Narrative Studies

Contents

1 Automatically Producing Plot Unit Representations for Narrative Text

[Goyal et al.(2010)Goyal, Riloff, and Daumé]
https://www.cs.utah.edu/~riloff/pdfs/emnlp10-plotunits.pdf

- Plot units were proposed in 1980 as a conceptual knowledge structure for representing and summarizing narrative stories. Can current NLP techniques produce Plot units automatically?
- Contributions
  - Created system AESOP exploits existing resources to identify affect states and applies ***projection rules*** to map the affect states onto the characters in a story.
  - Used corpus based techniques to generate a new type of affect knowledge base: verbs that impart positive or negative states onto their patients (e.g., being eaten is an undesirable state, but being fed is a desirable state). Harvested these ***patient polarity verbs*** from a web corpus using two techniques. **(a)** co-occurrence with Evil/Kind Agent patterns ***(b)*** Bootstrapping over conjunctions of verbs.
- Plot units (Lehnert' 1981) were used in narrative summarization studies, both in computer science and psychology. It previously relied on manual knowledge engineering. (Motivation of automation)
- AESOP identifies words that corresponds to positive, negative and mental affect states. It uses affect projection rules to map the affect states onto the characters in the story based on verb argument structure. Causal and cross-character links are created using simple heuristics.
- Plot units have 3 types of affect states a) positive b) negative and c) mental. Affect states get connectd by causal (same character and have 4 types: motivation, actualization, termination ,equivalence) and cross-character (single event affects multiple characters) links.
- Source of Affect States : a) Direct expression of emotions b) Situational affect states c) Plans and goals -¿ **direct expressions of plans/goals, speech acts, inferred plans/ goals, Plan/goal completion*
- AESOP works through 4 main steps.
  - Affect state recognition [using lexicons datasets, framenet, speech act verbs]
  - Character identification : Assumed only two characters per fable, both characters are in fables title. Hand-crafted a simple rule based coreference system. (Lots of assumptions.) Used wordnet to list gender specific lexicons.
  - Mapping Affect States onto Characters : Sundance parser was used to perform shallow performing of the sentence. Normalized verb phrases with respect to active/passive voice to simplify the rules. Assumed that the *Subject* of the VP is its AGENT and the Direct Object of the VP is its PATIENT. Developed 4 affect projection rules: a) AGENT VP b) VP PATIENT c) AGENT VP PATIENT d) AGENT VERB1 to VERB2 PATIENT.
  - **Inferring Affect States :**
- **Evaluation:** Fables have two desirable attributes: (1) they have a small cast of characters, and (2) they typically revolve around a moral, which is exemplified by a short and concise plot. Even so, fables are challenging for NLP due to anthropomorphic characters, flowery language, and sometimes archaic vocabulary.
  Collected 33 Aesop's fables from pacificnet.net.

2 Modeling Evolving Relationships Between Characters in Literary Novels

[Chaturvedi et al.(2016)Chaturvedi, Srivastava, III, and Dyer]
`https://www.aaai.org/ocs/index.php/AAAI/AAAI16/paper/viewFile/12408/12012`

- Hypothesized that relationships evolve with the progress of narrative and formulate the problem of relationship modeling as a structured prediction problem.
- **Related Works:**
  - Computational narrative studies : focuses on modeling the narrative from the perspective of a) events or b) characters.
  - Event based approaches includes **scripts, plot units, temporal event chain or schemas, bags of related events**.
  - Character based approaches attempts to **understand stories from the viewpoint of characters and relationships between them**. This perspective **explains the set of observed actions using characters personas or roles and the expected behavior of the character** in that role. Recent works focused on **constructing social networks**, sometimes **signed networks** to model the relationships between characters.
  - Bamman, O'Connor, and Smith (2013) presented two latent variable models for **learning personas in summaries of films by incorporating events that affect the characters**. In their subsequent work (Bamman, Underwood, and Smith 2014), they **automatically infer character personas in English Novels**. Similarly Valls-Vargas, Zhu, and Ontanon (2014) **extract character roles from folk tales based on their actions**. There have been other attempts towards **understanding narratives from view points of characters** (Chaturvedi, Goldwasser, and Daume 2015).
    Elson, Dames, and McKeown (2010) **constructed social networks of characters of British novels and serials by analyzing their dialogue interactions**. Their goals required them to model 'volume' of interactions rather than 'nature' of relationships.
    Leskovec, Huttenlocher, and Kleinberg (2010) proposed **signed social networks to model both positive and negative relationship**s, though they operate in **social media domain**. More recently, Krishnan and Eisenstein (2015) **analyze movie scripts to construct a signed social network depicting formality of relationships between characters**. Srivastava, Chaturvedi, and Mitchell (2015) construct **signed but static social networks from movie summaries**.
- Most of the relationships are romantic and it explains most of their mutual behavior.
- **Task :** Given a narrative and a pair of characters appearing in it, *Learn Relationship Sequences.*
- Proposed a **semi-supervised segmentation framework** for training on a collection of fully labeled and partially labeled sequences of sentences from narrative stories. The structured prediction model attempts to **model the narrative flow** in the sequence of sentences.
- **Contributions :** Problem formulations of relationship modeling, feature engineering, semi-supervised framework.
- **Relationship Prediction Model :** Given the narrative text in form of a sequence of sentences (in which the two characters of interest appear together), x = $(x_1, x_2, ..., x_l)$, we address the problem of segmenting it into non-overlapping and semantically meaningful segments that represent continuities in relationship status. Each segment is labeled with a -1 or +1. So it yields a relationship sequence r. Used **second order Markovian latent variable model** for segmentation and used them in the semi-supervised model.

- **Segmentation Model:** This core part of the framework assumes that each sentence in the sequence is associated with a latent state that represents its relationship status. Uses a rich feature set to analyze the contents of each sentences and simultaneously models the flow of information between states by treating the prediction task as a structured problem. Utilized a second order Markov model that can remember a long history of the relationship between the two characters and collectively minimizes the following linear scores for individual sequences. $score = \sum_i w_{\o}(x|y_i, y_{i-1}, y_{i-2})$ Error in equation in the paper.

  The model is trained using an averaged structured perceptron (Collins 2002). Uses Viterbi based dynamic programming algorithm. Slide `http://www.cs.columbia.edu/~mcollins/courses/6998-2012/lectures/lec5.1.pdf`

- **Semi-supervised Framework:** *(Not very clear).* Uses a two step algorithm.

- **Feature Engineering**

  - **Pre-processing:** POS tagging, dependency parsing, identify major characters and character names clustering using **Book-nlp pipeline***(Bammen, Underwood, Smith' 2014)*. Augmented its output using coreferences obtained using *CoreNLP*. *Frame semantic parse of the text using* ***Semafor*** *(Das et al. 2014).* Obtained connotation, sentiment and prior-polarity of words when needed during feature extraction.
  - **Content Features:**
    * **Action based(verbs) :** Motivated by a theory 'characters have a sphere of actions'. Modeled actions affecting the two characters by identifying all verbs in the sentence, their agents and their patients. Used dependencies to find out these relations. Considered conjunctions, negations.
    * Adverb based
    * Lexical
    * **Semantic Parse based:** Manually compiled a list of positive,negative, ambiguous and relationship frames and relevant frame elements. Extracted two features. Counts of frames fired with(1) and without (2) at least one character.
  - **Transition Features:** Remembers relationship histories. (If else tree)

- **Dataset:** *SparkNotes*:300 English novels plot summaries (Extracted and annotated sequences), AMT (Crowdsourced. Annotated binary labels for each relationship timeline of character pairs.). 62 pairs of characters overlap with SparkNotes.

- **Baselines:** (1) Flat classifier using only the content features to test the hypothesis that relationship sequence prediction is a structured problem. (2) Second order Markovian segmentation model to understand the importance of remembering a long history of relationships between characters. *Evaluated in both sentence and sequence level. (P,)*

3 Toward Character Role Assignment for Natural Language Stories

[Valls-Vargas et al.(2013)Valls-Vargas, Ontanón, and Zhu]
https://pdfs.semanticscholar.org/4126/6463134db123f99ecca9dddee0c4f5157613.pdf

- NLP + Propp's morphology of the folktale = Method for automatically assigning narrative roles to characters in stories.
- Narrative text follows conventions such as genres and exhibit recur- ring patterns. For example, Russian folktales generally have heroes and villains, and the actions these villains make are often malicious. At the structural level, there is certain regularity in terms of how different narrative events in these folktales are organized.

4 Unsupervised Learning of Evolving Relationships Between Literary Characters

[Valls-Vargas et al.(2013)Valls-Vargas, Ontanón, and Zhu]
https://cs.umd.edu/~miyyer/pubs/2017_relationships_aaai.pdf

- Unsupervised approach that models relationships as dynamic phenomenon, represented as evolving sequences of latent states empirically learned from data. Unlike previous paper (polarity in relationships), it models dynamic states.
- **Dataset:** 300 English novel-summaries. Identified major characters in these summaries, and pairs of characters that appeared together in more than 5 sentences were considered for analysis. Final dataset contained 634 such sequences, with an average length of 8.2 sentences per sequences. Vocabulary size 10K. After feature extraction, it became 4.2K. Trained word embeddings on Gutenberg books (D=200).
- **Feature Extraction:** Given a narrative text and and two characters appearing in it, the goal is to represent their relationship as a sequence of latent variables. **Considered the sentences where two characters appeared together.** Represented each sentence as a feature vector. *Task of the model is to assign a discrete latent state to each feature vector.*
  - Preprocessed using the BookNLP pipeline to obtain **POS tags, dependency parses and co-referent mentions and to identify major characters.** Also obtained **Framed semantic parses**.
- **Actions:** Represented inter-character relationships using their actions (done to each other). Identified verbs and their agents using *nubj and agent* and patients using *dobj and nsubjpass* relations. Also considered verbs conjoined with each other with a *conj* relation. So for each of the sentences, a set of verbs was extracted where each verb has one agent and one patient.
- *Surrogate Actions* using another set of verbs which have either of the two characters as the agent or patient, *BoW*, *Frame Semantic parse* (e.g. Triggers *personal relationship* for the token *friendship*).
- **Models**
  - **GHMM**, a non-Bayesian Hidden Markov Model with Gaussian Emissions. The hidden states comprise of relationship states and vector representation of sentences form the observations.
  - **Penalized HMM**, which extends GHMM by smoothing the relationship sequences and discouraging frequent changes in relationship states within a sequence.
  - **Globally Aware GHMM**, attempts to simulate the intuition of a global belief about the relation- ship between the characters, while analyzing the individual sentences of the sequence.
- **Evaluation:** 4 approaches
  - Used a manually annotated dataset (assuming binary relationship types)
  - Human judgment in characterizing relationships
  - If the learned categories are semantically coherent
  - Previously proposed approach (Iyyer et al. 2016)
- **The Globally aware GHMM performed better than others.**

5 Learning Latent Personas of Film Characters

[Bamman et al.(2013)Bamman, O'Connor, and Smith]
`http://repository.cmu.edu/cgi/viewcontent.cgi?article=1179&context=lti`

- Presented two latent variable models for learning character types or personas. **Persona is defined as a set of mixtures over latent lexical classes.** Lexical classes are basically **actions** where each action typically has an agent and a patient.
- Research questions : a) Can we learn what standard personas are by how individual characters are portrayed? b) Can we learn the set of attributes and actions by which we recognize those common types? How do we recognize a VILLAIN?
- Dataset
  - 42,306 movie plot summaries extracted from Wikipedia.
  - Median length of 176 words. Top 1000 movies by box office revenue have a median length of 715 words.
  - Used CoreNLP to extract entities, tag and syntactically parse the text and resolve co-reference within the document.
  - Extracted features are *Agent Verbs, Patient Verbs, Attributes*.
  - Metadata (detailed genre, actors information like name, age) collected from Freebase (now closed).
- **Persona:** A characters latent type can have 3 properties. *Actions they do (VILLAINS kill), Actions done to them (VILLAINS get arrested) and Attributes of them (VILLAINS are evil)*. Defined *Persona* as a set of three typed distributions.

6 PersonaBank: A Corpus of Personal Narratives and Their Story Intention Graphs

[Lukin et al.(2016)Lukin, Bowden, Barackman, and Walker]
`http://www.lrec-conf.org/proceedings/lrec2016/pdf/356_Paper.pdf`

- A new corpus of 108 personal narratives annotated with a deep representation of narrative (raw material) called a STORY INTENTION GRAPH (SIG). Story types are romance, travel, sports, holidays, watching wildlife and weather. Also annotated for overall polarity of tone.
  The SIG representation provides a propositional representation of the story timeline, the goals and motivations of the story characters.
- Used the DramaBank language resource (a collection of Aesop's Fables and other classic stories that utilize the SIG representation (Elson and McKeown, 2010; Elson, 2012a; Elson, 2010)).
- The SIG is an abstract model of narrative structure that was designed to be able to represent any story in terms of its characters, and their actions, intentions and affectual motivations.
- Several practical advantages to using the SIG representation for our corpus:
  - DramaBank comes with an annotation tool called Scheherezade that produces the STORY INTENTION GRAPH. Previous research and our own experience suggest that it is easy to train naıve annotators to annotate stories with Scheherezade.
  - Scheherezade includes a natural language generator that outputs a retelling of the original story that reflects the annotators' decisions.
  - Many of the stories share similar themes, topics and activities that allow us to understand the common plot structures across stories with similar SIG representations.
  - The SIG allows for the experimentation of producing variations in narrative structure for the same story and exploring stylistic differences in discourse structure and story tellings.
- The corpus will be useful to other researchers interested in everyday storytelling, narrative modeling, language generation, and language processing
- STORY INTENTION GRAPH (Watch figure 2 in the paper)
  - Built to find computational models that look beyond the surface form of a text to compare and contrast stories based on content, as opposed to style (Elson, 2012b). The STORY INTENTION GRAPH, or SIG, formalism is robust, emphasizing key elements of a narrative rather than attempting to model the entire semantic world of the story. It is an expressive and computable model of content that is accessible for human subject to use an annotation methodology to create an open-domain corpus.
  - Contains 4 layers
  - The first dimension of the SIG is called the "timeline layer", in which the story facts are encoded as predicate-argument structures (propositions) and temporally ordered on a timeline. The timeline layer consists of a network of propositional structures, where nodes correspond to lexical items that are linked by thematic relations.
  - The second dimension is called the "interpretive layer" which captures the interpretations of why characters are motivated to take the actions they do. This layer goes beyond summarizing the actions and events that occur, and attempts to capture story meaning derived from agent-specific plans, goals, attempts, outcomes and affectual impacts. Here, the SIG uses predicates (discourse relations) that signify plans and goals.

  - The final dimension (fourth column in Figure 2) is the "affectual" layer. Here, affect relations and are represented by the arcs between story elements.
  - There are a fixed number of types of arcs and affectual nodes that can be used to annotate any kind of story in the interpretation layer.

- 108 stories were collected from the Spinn3r corpus and annotated for story topic (Burton et al., 2009)

- Used lucene to find pre-defined topic related stories. Manually checked if a story is of a certain topic. 55 have positive and 53 have negative polarity. Average number of words is 269.

- **Scheharazade** is a free tool to annotate SIG.

  - Characters and props are identified
  - Actions and properties are assigned to the characters and props. Story points are created by highlighting texts from the story and finally these story points create a timeline layer and make up a network of propositional structures.
  - This tool uses the predicate-argument structures from the VerbNet lexical database and uses WordNet as its noun and adjectives taxonomy.

- **Applications**

  - SIG representations have been used in applications related to storytelling, game playing and narrative studies.
  - (Harmon and Jhala, 2015) used SIG and **Skald** in parallel for narrative generation. **Skald** is a narrative generator.
  - SIGs are beneficial as a content planner. (Antoun et al., 2015) has used the SIG as an intermediate representation of meaning by transforming a play trace of the PromWeek game into a representation which can be used to generate natural language recaps of the game.
  - Story dialogue with gesture corpus by (Hu et al, 2016) used SIG.
  - The Expressive-Story Translator (EST) explores the use of personal narratives in storytelling by utilizing the rich representation of SIGs. * Some related works are mentioned in the paper.

7 Multi-Label Sparse Coding for Automatic Image Annotation

[Wang et al.(2009)Wang, Yan, Zhang, and Zhang]
`https://pdfs.semanticscholar.org/a326/1a1f0489ae4d782faa007617a4e479bde738.pdf`

- **Dataset**
  - **Corel5k:** 5K images from 50 Stock Photo CDs. Each CD includes 100 images on the same topic.Each image is annotated with **1 to 5** keywords. Total 374 keywords. 4500 train, 500 test.
  - **Corel30k:** Extension of Corel5k. 32,695 images and 5,587 keywords. Keywords (950) with **at least 10 images**.
- **Evaluation:** Used top 5 annotations based on posterior probability.
  - Performance was measured using the precision and recall of every keyword.
    Recall of word w_i = Number of images correctly annotated with w_i / Total image with annotated with w_i in dataset.
    Precision of word w_i = Number of images correctly annotated with w_i / Total image with annotated with w_i by model.
    Both measures were averaged over the set of keywords that appear in the testing set.
  - *Considered the number of words with **nonzero recalls***. Indicates how many words the system effectively learned.
  - Semantic Retrieval Performance

8 Improving Event Detection with Abstract Meaning Representation

[Li et al.(2015)Li, Nguyen, Cao, and Grishman]
http://www.aclweb.org/anthology/W15-4502

- AMR represents the meaning of a sentence encoded as a rooted, directed and acyclic graph.
- Focused on the event detection task defined in Automatic Content Extraction (ACE) evaluation [1]. The task defines 8 event types and 33 subtypes such as *Die* and *End-Position*. ACE 2005 annotation guideline presented this example sentence for systems to detect event.
  "A bomb **exploded** in central Baghdad yesterday."
  Here "exploded" is a trigger for the event *Attack* and an event detection system should detect that.
- AMR can make an abstract representation of semantically similar terms presented with different lexicons that can benefit a system to detect events.
- Used Maximum Entropy classifier with existing features and also the new features from AMR.
- Features extracted from AMR (More were tested).
  - amr_word_tag : candidate word + AMR tag
  - amr_dist_to_root : distance between the candidate word and the root
  - amr_parent_word : Word of the parent node
  - amr_parent_tag : AMR tag of the parent node
  - amr_parent_word_tag : parent word + AMR tag
  - amr_sibling_tag : AMR tag of each sibling node
  - amr_sibling_word_tag : sibling word + AMR tag
  - amr_child_word_tag : child word + AMR tag
  - amr_grandchildren_word : word of the grandchildren node
- Evaluated over the ACE 2005 corpus. Train/Dev/Test : 529/30/40 documents, 14,849/836/672 sentences.

[1] http://projects.ldc.upenn.edu/ace/

9 Abstract Meaning Representation for Sembanking

[Banarescu et al.(2013)Banarescu, Bonial, Cai, Georgescu, Griffitt, Hermjakob, Knight, Koehn, Palmer, and Schneider]
`http://www.aclweb.org/anthology/W13-2322`

- AMR - Semantic representation language
- Penn Treebank is an inspiration behind this work. Penn Treebank motivated to build statistical parsers that improve in accuracy each year. To improve this parser, some related problems like base noun identification, prepositional phrase attachment, trace recovery, verb-arguement dependencies etc are being solved.
- Overall state of semantic annotations is not organized well. There are separate annotations for NER, coreference, semantic relations, discourse connectives, temporal entities etc. Each annotation has its own associated evaluation and training data is split across many resources. No sembank of english sentences and their meaning representation is available.
- Expectation is way to new work in statistical NLU. It will help to build better semantic parsers that are as ubiquitous as syntactic ones. It will also be helpful to support generation as AMR will be able to provide a logical semantic input.
- Basic Principles
  - AMR tries to ignore syntactic variations and provide same representations for sentences with same meaning. For example, the sentences "he described her as a genius", "his description of her: genius", and "she was a genius, according to his description" are all assigned the same AMR.
  - AMR uses of PropBank framesets to create abstract representation of lexicons.
  - Absence of any rule sequence for parsing sentences to AMR makes sembanking faster.
  - AMR is heavily biased towards English. It is not an Interlingua.
- Contents in the paper contains different labels, structure in graphs and tree format
- Limitations
  - AMR doesn't represent inflectional morphology for tense and number, and it omits articles.
  - No universal quantifier. Doesn't distinguish between real events and hypothetical, future, or imagined ones.

10 Multilabel Text Classification for Automated Tag Suggestion

[Katakis et al.(2008)Katakis, Tsoumakas, and Vlahavas]
`http://www.aclweb.org/anthology/W13-2322`

- System description for participating ECML/PKDD 2008 Discovery Challenge for tag recommendation.
- Limitation of collaborative tagging :
  - Users can describe the same object based on different granularity. It depends on users personal opinion, knowledge background and preferences. It makes the tag space noisy and finding material tagged by other users becomes harder.
  - People may use words that have many related senses as tags. This can lead to inappropriate connection between items and tags.
  - Different tags can be synonymous that increases data redundancy.
  - People tend to assign a small number of tags to an object. It creates an incompleteness.

  Motivation is to develop methods that can suggest appropriate rich set of tags.
- Dataset was build using the data from Bibsonomy: a social bookmarking and publication-sharing system. People can assign tags to webpages and bibtex entries. Average tags per item is 3.25 and average tags assigned by a user to an item is 2.76 in the test portion (20%).
- Multilabel classification process : If item appears in the training set (tracked by id), most popular tags for the item are suggested. If the item not appears in the training set, the system checks if the user has appeared before. It user is found, most popular tags for that user are suggested. Otherwise multilabel classifier is called to assign relevant tags.
- Model takes 3 parameters. Text representation (BoW), Max number of recommendation, Minimum confidence score.
- For bookmarks of web pages 208 tags and 2150 words. For bibtex files 159 tags and 1836 words.
- Used Binary Relevance classifier with Naive Bayes from the Mulan package. Separate classifiers for bibtex and web page item.
- Average F-measure for evaluation. Best was 0.0852.

11 Tag Recommendation for Folksonomies Oriented towards Individual Users

[Lipczak(2008)]
`https://www.kde.cs.uni-kassel.de/ws/rsdc08/pdf/10.pdf`

- System description for participating ECML/PKDD 2008 Discovery Challenge for tag recommendation.
- Contains related works on tag recommendations
-

12 Skip-Gram – Zipf + Uniform = Vector Additivity

[Gittens et al.(2017)Gittens, Achlioptas, and Mahoney]
`https://www.aclweb.org/anthology/P/P17/P17-1007.pdf`

- Word embeddings exhibit compositionality. e.g. Man+Royal = King. This paper tries to find the theoretical justification of this. Why does it happen? Also explains the success of vector calculus in solving word analogies.
  Connects Skip-gram model and the Sufficient Dimensionality Reduction (SDR) framework of Globerson and Tishby.
-

13 Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

[Socher et al.(2013)Socher, Perelygin, Wu, Chuang, Manning, Ng, and Potts]
https://nlp.stanford.edu/~socherr/EMNLP2013_RNTN.pdf

- Semantic composition for longer phrases is a difficult task and requires lot of resources. Sentiment Treebank contains fine grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences. Presented Recursive Neural Tensor Network. Accuracy on polarity classification is 85.5% compared to the state of art 80%. Accurately predicts the effects of negations.
- **Related Works**:Semantic vector spaces, Compositionality in vector spaces (several interesting approaches), Logical form (old technique worked well in closed domain), Deep Learning.
- Binary classification performance is 80% using BoW. For multicalss its 60% on twitter data. Word order and considering negations are the problem.
- Used movie review corpus from Pang and Lee (2005), collected capitalized version, parsed, labeled phrases (Very Negative, Negative, Somewhat negative, Neutral, Somewhat positive, Positive, Very Positive) using AMT.
- **Recursive Neural Model**: These models usually work in a bottom up fashion to create a tree. They take vector representations of two words and a function compose the parent node for them. Then the parent node and the previous/next word are used to compose another parent node and this process goes on until whole sentence is traversed and forms a tree structure. They can compute compositional vector representation for phrases of variable lengths and syntactic types. Explained 4 different models of this structure.

  * RNN : Recursive Neural Network
  * MV-RNN: Matrix-Vector RNN
  * RNTN:Recursive Neural Tensor Network
  * Tensor Backprop through Structure

14 EXPLORING MOOD METADATA: RELATIONSHIPS WITH GENRE, ARTIST AND USAGE METADATA

https://pdfs.semanticscholar.org/4421/83b2518696b0ce86e818509373990c7f69c0.pdf

- Explored relationships of moods with genre, artist and usage metadata
- All Music Guide (website of metadata) dataset
- AMG dataset 179 mood tags from professional editors. Data sparseness problem 3 sets. Whole set, Popular sets, Clustered set.
- Co-occurence matrix to pearson correlation matrix. Agglomerative hierarchical clustering using Ward's criterion. Manually examined the clusters and found 29 of the 40 tags groups into 5 clusters.
- Showed relation analysis between mood tags and genre, artists, listening time (usage)

15 Music mood classification using arousal-valence values

http://icact.org/upload/2011/0386/20110386_finalpaper.pdf

- Music mood classification system based on arousal and valence score for music recommendation.
- Kate Hevner examined 6 musical features (tempo, pitch, mode, rhythm, harmony, melody) affective scores and tried to find out how they relate to the mood.
- Basically plotted 67 adjectives on AV plane and divided into 8 regions. (Other related works..). Robert Theyar's energy stress model.
- For 446 tracks, collected arousal and valence values from 10 paid persons.
- Grouped the tags into 8 groups.
- Classified using K-means.

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