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Mapping music notes to socio-political events

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- Mathematical tools for audio feature extraction
- Machine learning techniques
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Background

- Musical genres are labels created to characterize different types of music.
- Categorising using musical genres was carried out manually by humans.
- Automatic musical genre classification: an increased interest recently as one of the cornerstones of the general area of Music Information Retrieval.

Background

- Music has a significant cultural and political impact on real-world events bringing positive change and unity into the cultural and political world.

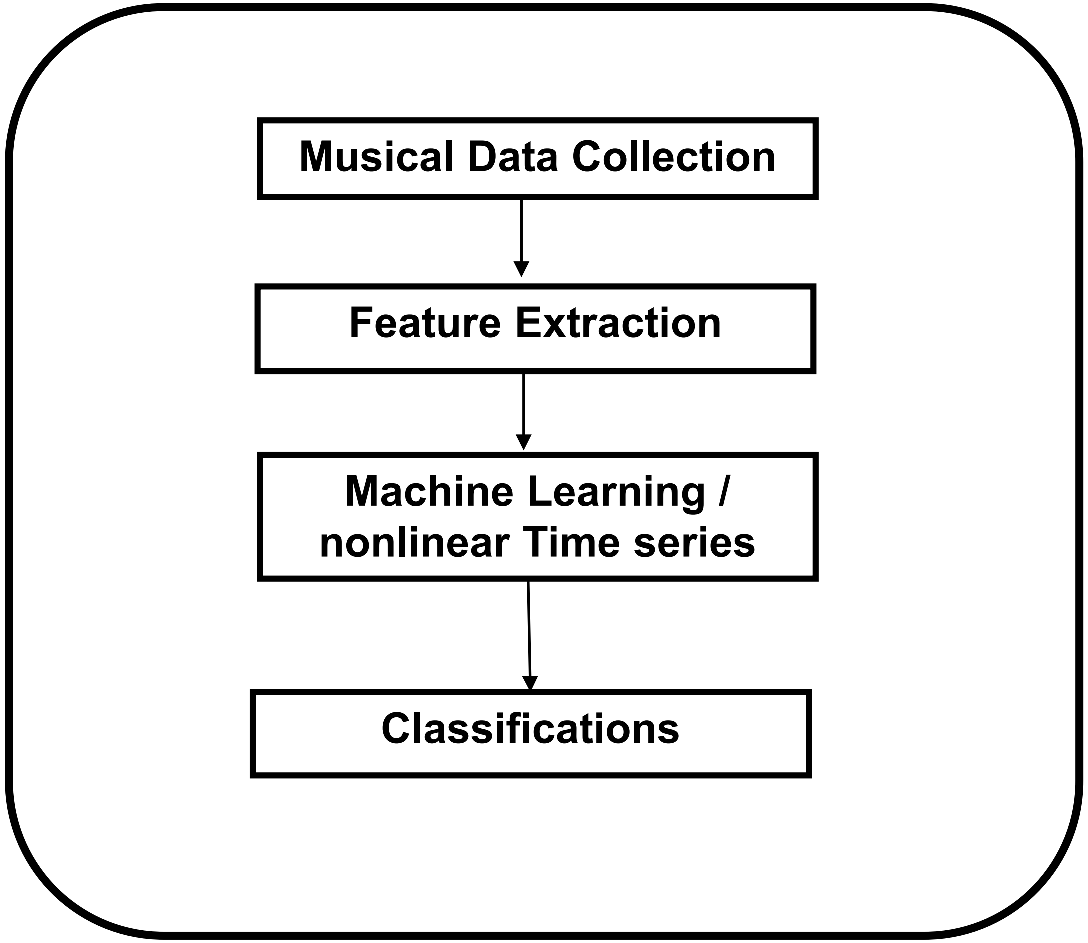
Background

- Aims of this work

(1) Automatic musical genre classification.

(2) Mapping music notes to socio-political events.

Background

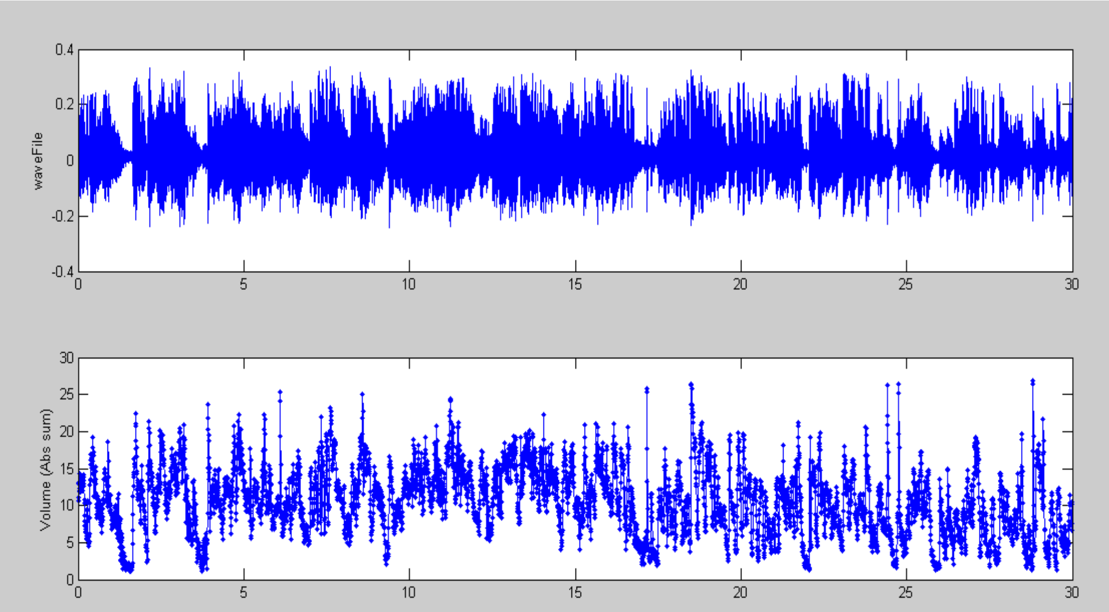

Musical Data Collection
Feature Extraction
Machine Learning / nonlinear Time series
Classifications

Audio features extraction

- Audio data are time series.
- y-axis is the current amplitude corresponds to the loudspeaker’s membrane.
- x-axis denotes time.

Audio features extraction: volume

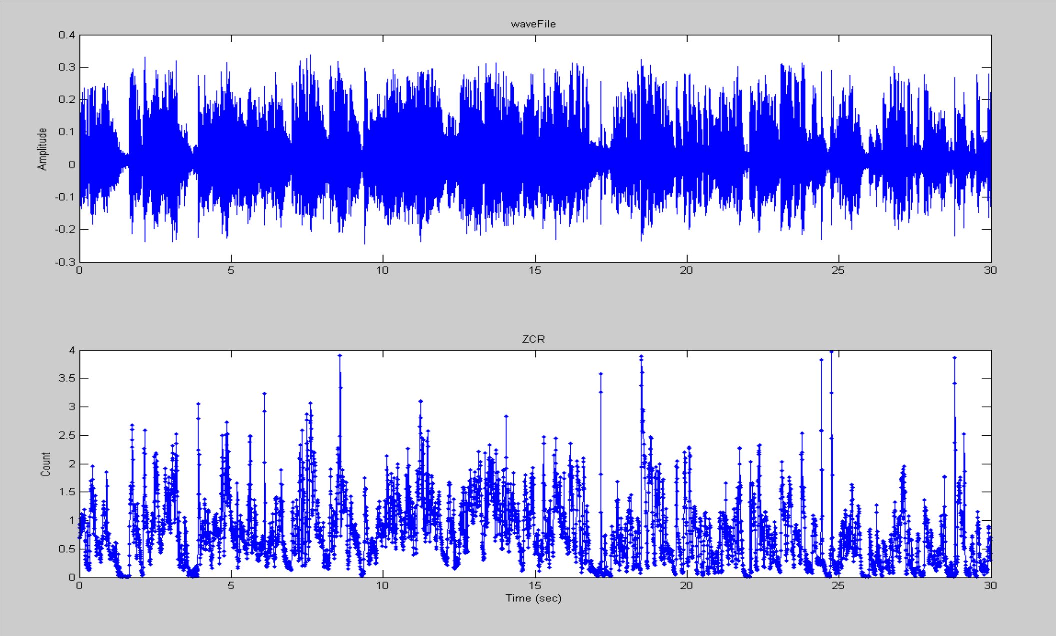
- Amplitude of the signals, also referred to as energy or intensity of audio signals. The sum of absolute sample, s, values for each frame, i, is given by Volume $= \sum_{i=1}^{n} |s_i|$



Sample sound amplitude (top) and computed volume of the sample (bottom).

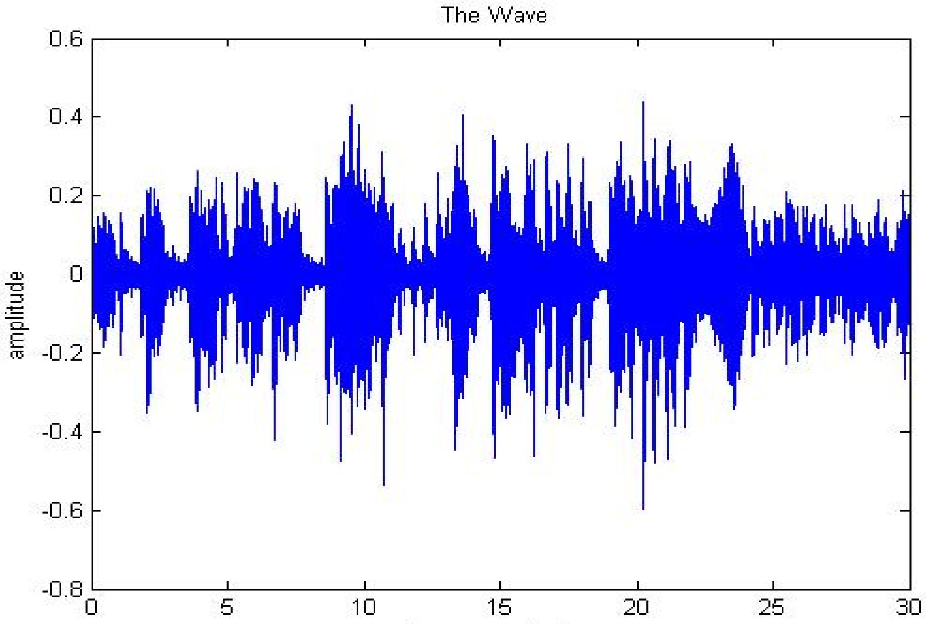
Audio features extraction: zero-crossing rate

- The rate of sign-changes along a signal. This feature has been used in both speech recognition and music information retrieval.



Audio features extraction: frequency domain

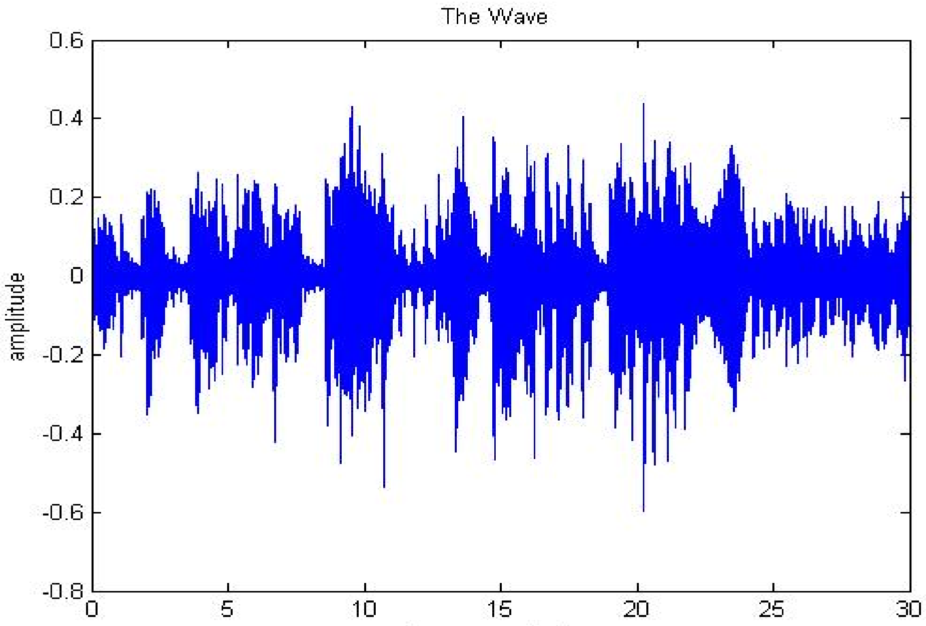
- A given signal can be converted between the time and frequency domains using Fast Fourier Transform (other techniques include the wavelets



Sample sound amplitude with a duration of 30 seconds

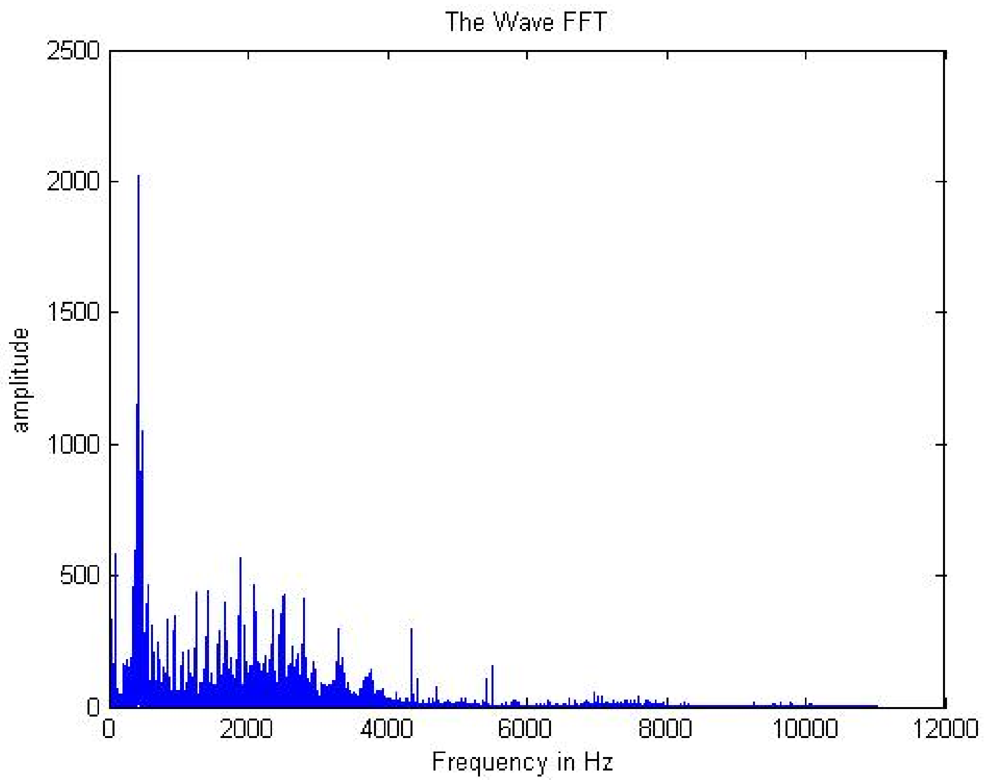
Audio features extraction: frequency domain

- A given signal can be converted between the time and frequency domains using Fast Fourier Transform (other techniques include the wavelets transform and etc.).



Sample sound amplitude with a duration of 30 seconds

Audio features extraction: frequency domain



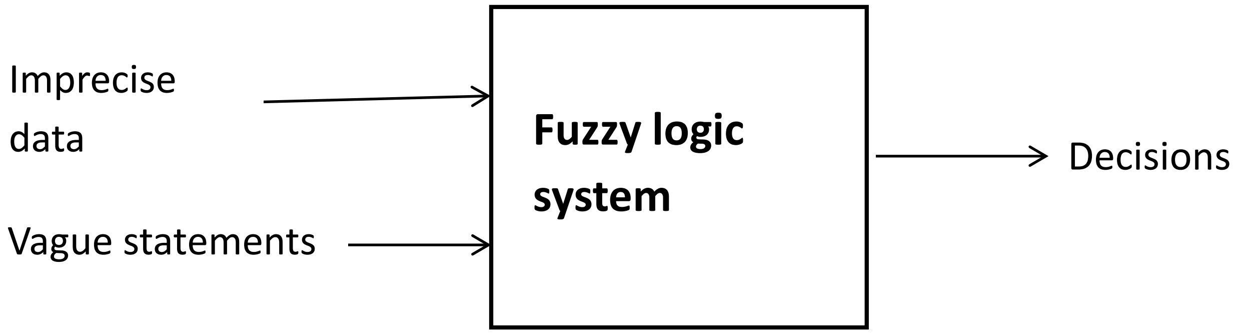
The sampled amplitude in the frequency domain by applying FFT to the sample sound amplitude in the previous figure.

Machine learning techniques

- System modelling based on conventional mathematical tools, such as differential equations, emphasize a precise description of physical quantities and fail to achieve satisfactory results when dealing with ill-defined and uncertain systems.
- Fuzzy inference: model the qualitative aspects of human knowledge and reasoning processes without precise quantitative analyses

Machine learning techniques: fuzzy logic

- A multi-valued logic that permits intermediate values to be determined between standard assessments like yes/no, true/false, right/wrong, etc.



Machine learning techniques: fuzzy logic

- Mamdani fuzzy model

A Mamdani fuzzy model of a system with r rules is as shown below:

$$R_i\text{: if } X \; is \; A_i \text{ then } Y \text{ is } B_i, i = 1,2, \ldots, r$$

where

X is A_i - Antecedent proposition of the rule.

Y is B_i - Consequent proposition of the rule.

X is the input variable.

Y is the output variable.

Machine learning techniques: fuzzy logic

- Takagi-Sugeno (TS) model

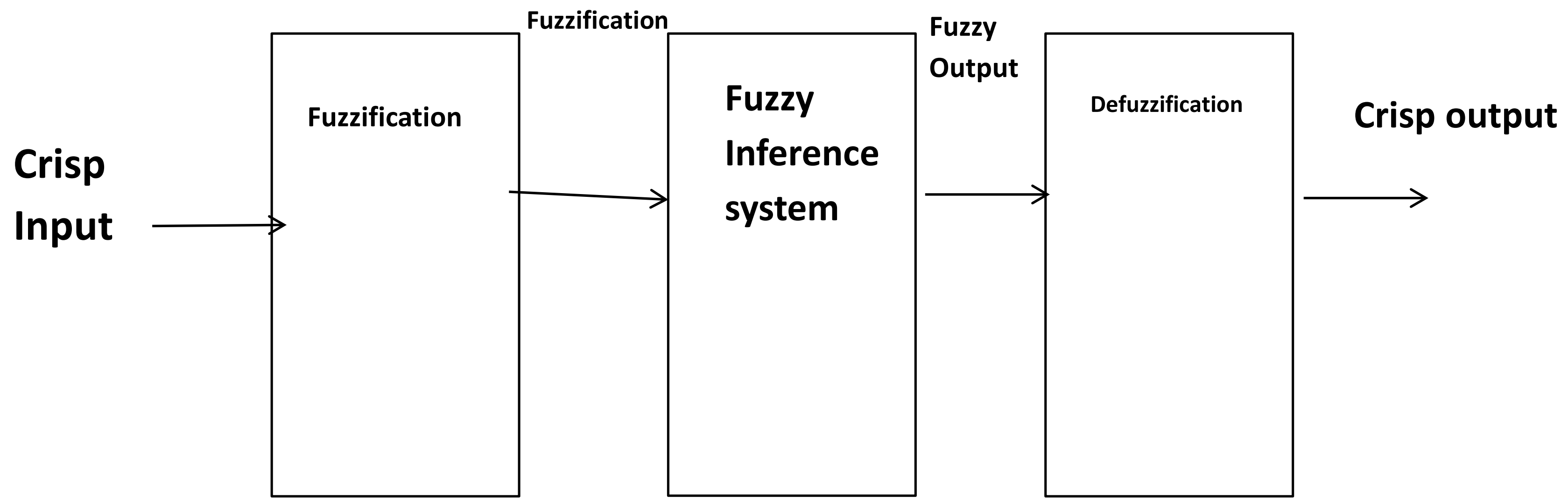
The antecedents are fuzzy sets and the consequents are crisp functions of the antecedent variables. A TS model of a system with r rules is for instance:

$$R_i : \text{ if } X \text{ is } A_i \text{ then } Y_i = f_i(X), i = 1,2, \dots, r$$

where $f_i(X)$ is a function of the antecedent variables.

Machine learning techniques: fuzzy logic

- A typical fuzzy system



Machine learning techniques: neuro-fuzzy modelling

Building intelligent system: Fuzzy logic and neural networks.

- Neural networks: Good for recognising patterns but poor at explaining the decision making process.
- Fuzzy logic systems: Good at explaining decisions but unable to automatically acquire the rules and membership functions.
- Neuro-fuzzy system: Functionally equivalent to a fuzzy inference system; No prior knowledge of rules and membership function; Can be trained to develop fuzzy rules and determine membership functions for the input and output variables of the system.

Machine learning techniques: neuro-fuzzy modelling

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Jang J.S.R. *ANFIS: adaptive-network-based fuzzy inference system*. IEEE Trans Systems Man Cybern. **23**(3): 665–685, 1993.

Our first attempt is to implement this ANFIS with applications to music and socio-political events.

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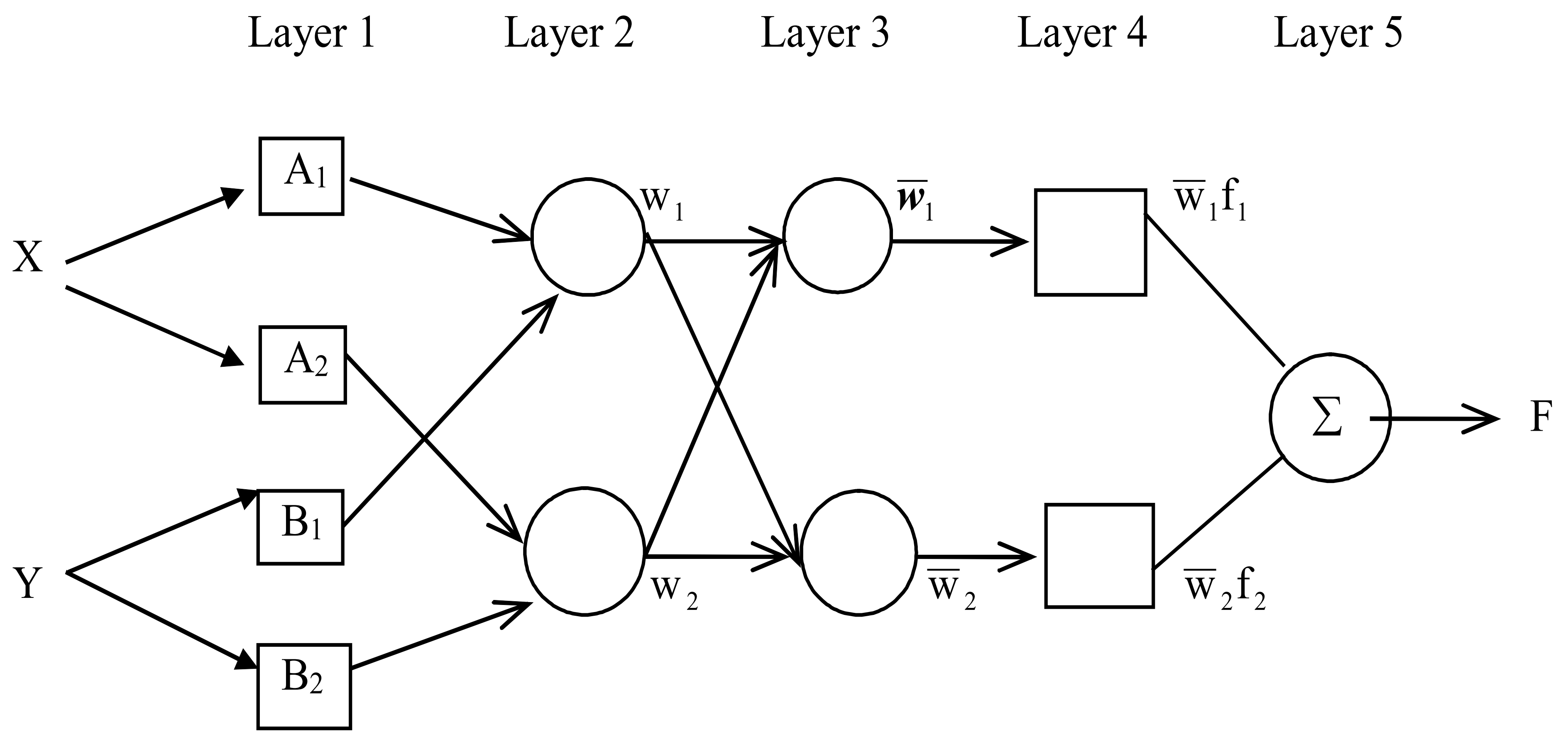
Machine learning techniques: neuro-fuzzy modelling

- First layer: An input layer representing fuzzy membership functions
- Second and third layers: Contain nodes that provide the antecedent parts in each rule.
- Fourth layer: Computes the first-order Takagi-Sugeno rule output for each fuzzy rule.
- Fifth layer: Computes the weighted global output of the system.

Machine learning techniques: neuro-fuzzy modelling



Music genre classification

- Based on the ANFIS we implemented one fuzzy neural system tailored to classify a song or a short sound clip into its corresponding music genre.
- The algorithm has wo phases:

  (1) feature extraction technique,

  (2) model implementations.

Music genre classification

Six features have been used

Short Time Energy – Energy of the signal in each analysis frame/window

Spectral Centroid – Centre of gravity of the magnitude spectrum of the Fourier transform

Zero-crossing – Mean of zero crossings across time frames in the texture window

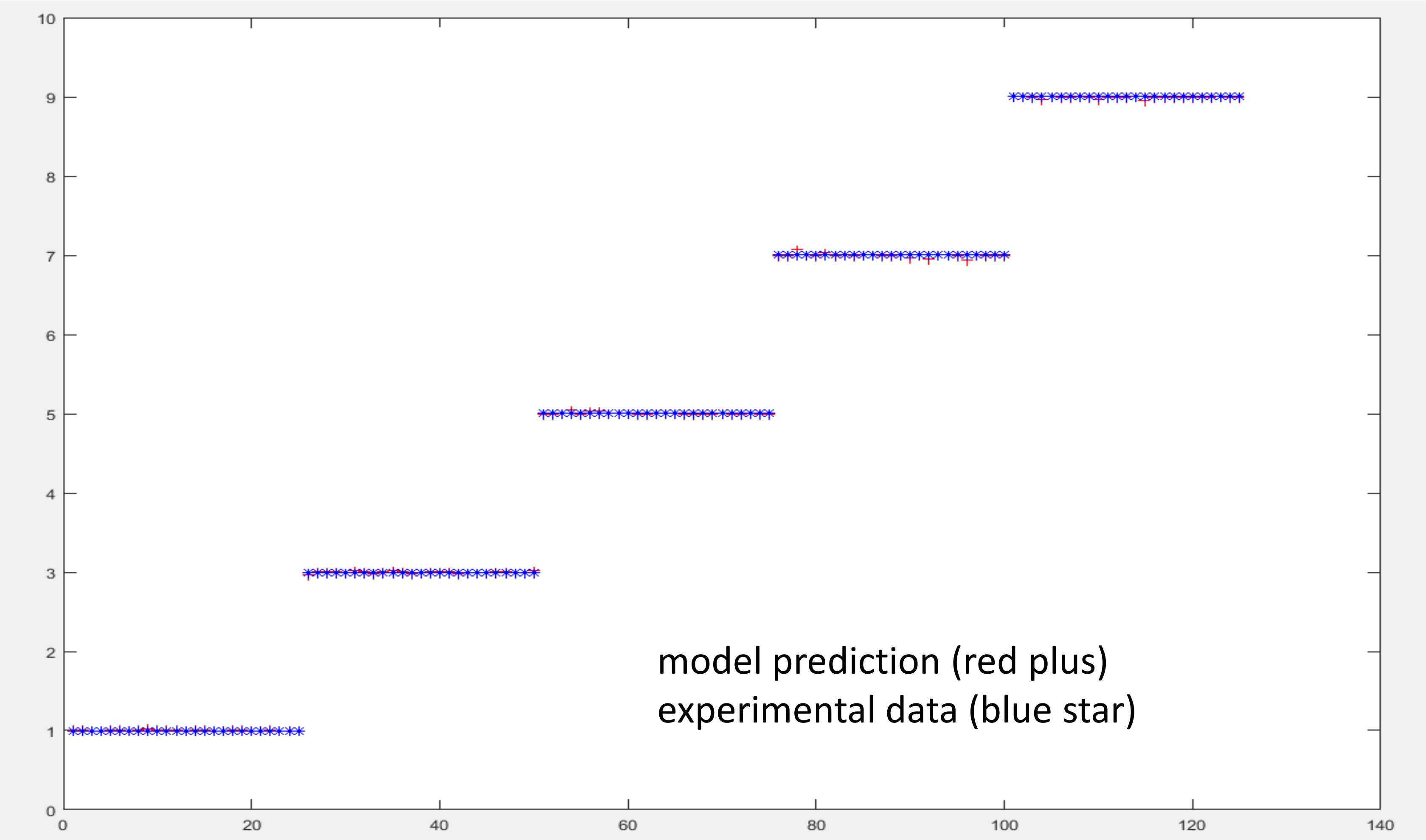
Spectral Flux – The squared difference between the normalized magnitudes of successive spectral distributions

Spectral Rolloff – Frequencies that are below 85% of the magnitude distribution

Music genre classification

- Database: Music includes blues, classical, country, disco and pop.
- To examine automatic music genre classification methods described above.
- We have used 125 songs as experimental data represented by the x-axis in the figure below.
- The genres 1, 3, 5, 7 and 9 represents blues, classical, country, disco and pop, respectively.
- The model is used to predict the genres provided the songs.

Music genre classification



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Predicting socio-political events

- Correlation between the popular music prior to election and the outcome of the election?
- Implication: A dependency of the election results on the popular music.

Year	Std - Energy Entropy	Std - ZCR	std-SpectralRollOff	Std - Spectral Centroid	Std - Spectral Flux	Std - Energy	Party
2009	0.019	0.1799	0.0018	0.0121	2.051	1.329	C
2004	0.0213	0.2242	0.0019	0.0234	2.347	1.7277	L
2004	0.0227	0.2103	0.0017	0.0212	3.3013	1.9094	L
2004	0.0163	0.3196	0.0022	0.0167	2.2703	0.939	L
2004	0.0215	0.0563	0.0017	0.0104	1.9904	1.6226	L
2000	0.0121	0.3552	0.0022	0.0157	1.2425	0.5036	L
2000	0.0251	0.1543	0.0017	0.0224	2.5768	2.4328	L
2000	0.0178	0.0584	0.0017	0.0084	1.9915	1.1332	L
1996	0.0132	0.399	0.002	0.0135	1.7606	0.5938	L
1996	0.0156	0.2255	0.002	0.0155	1.3865	0.7983	L
1996	0.0278	0.2145	0.0021	0.024	1.6228	3.1674	L
1996	0.0188	0.0948	0.0017	0.0108	1.5663	1.1388	L
1996	0.0307	0.2284	0.0018	0.0222	1.9502	4.1917	L
1996	0.0238	0.1825	0.0018	0.0232	2.7153	2.0545	L
1991	0.0185	0.0523	0.0018	0.0088	1.7118	1.1822	C
1991	0.0205	0.25	0.0018	0.0122	1.1269	1.5556	C
1991	0.0117	0.1442	0.0017	0.0142	1.5424	0.4685	C
1986	0.0543	0.1468	0.0013	0.0171	2.4987	21.2149	C
1982	0.0136	0.1501	0.0018	0.0167	1.615	0.6481	C
1978	0.0253	0.2679	0.0021	0.0177	1.9821	2.4001	C
1973	0.0183	0.2571	0.0019	0.019	2.1738	1.2213	L
1973	0.0235	0.5986	0.0024	0.0273	1.686	2.454	L
1973	0.0222	0.1842	0.0016	0.0245	3.3922	1.8606	L
1973	0.0127	0.1256	0.0019	0.0124	1.394	0.5509	L
1969	0.0228	0.1416	0.0022	0.0109	1.4147	2.2558	C
1969	0.0223	0.3236	0.0018	0.0217	2.6842	2.0182	C

Training data (C – Conservatory party) and the model prediction (L – Labour came to power).

position	Artist	Title
01	Archies	Sugar Sugar
02	Beatles With Billy Preston	Get Back
03	The Rolling Stones	Honky Tonk Women
04	Peter Sarstedt	Where Do You Go To (My Lovely)
05	Jane Birkin & Serge Gainsbourg	Je T'Aime... Moi Non Plus
06	Marvin Gaye	I Heard It Through The Grapevine
07	Creedence Clearwater Revival	Bad Moon Rising
08	Fleetwood Mac	Albatross
09	Frank Sinatra	My Way
10	Bobbie Gentry	I'll Never Fall In Love Again
11	Dean Martin	Gentle On My Mind
12	Zager & Evans	In The Year 2525
13	Elvis Presley	In The Ghetto
14	Marmalade	Ob-La-Di Ob-La-Da
15	The Beatles	The Ballad Of John And Yoko
16	Tommy Roe	Dizzy
17	Robin Gibb	Saved By The Bell
18	Thunderclap Newman	Something In The Air
19	Mary Hopkin	Goodbye
20	Fleetwood Mac	Oh Well
21	Desmond Dekker & The Aces	The Israelites
22	Kenny Rogers & The First Edition	Ruby Don't Take Your Love To Town
23	Donald Peers	Please Don't Go
24	The Bee Gees	Don't Forget To Remember
25	Plastic Ono Band	Give Peace A Chance

Data has been collected on the popular music one year prior to the election. Only 1969 is shown here.

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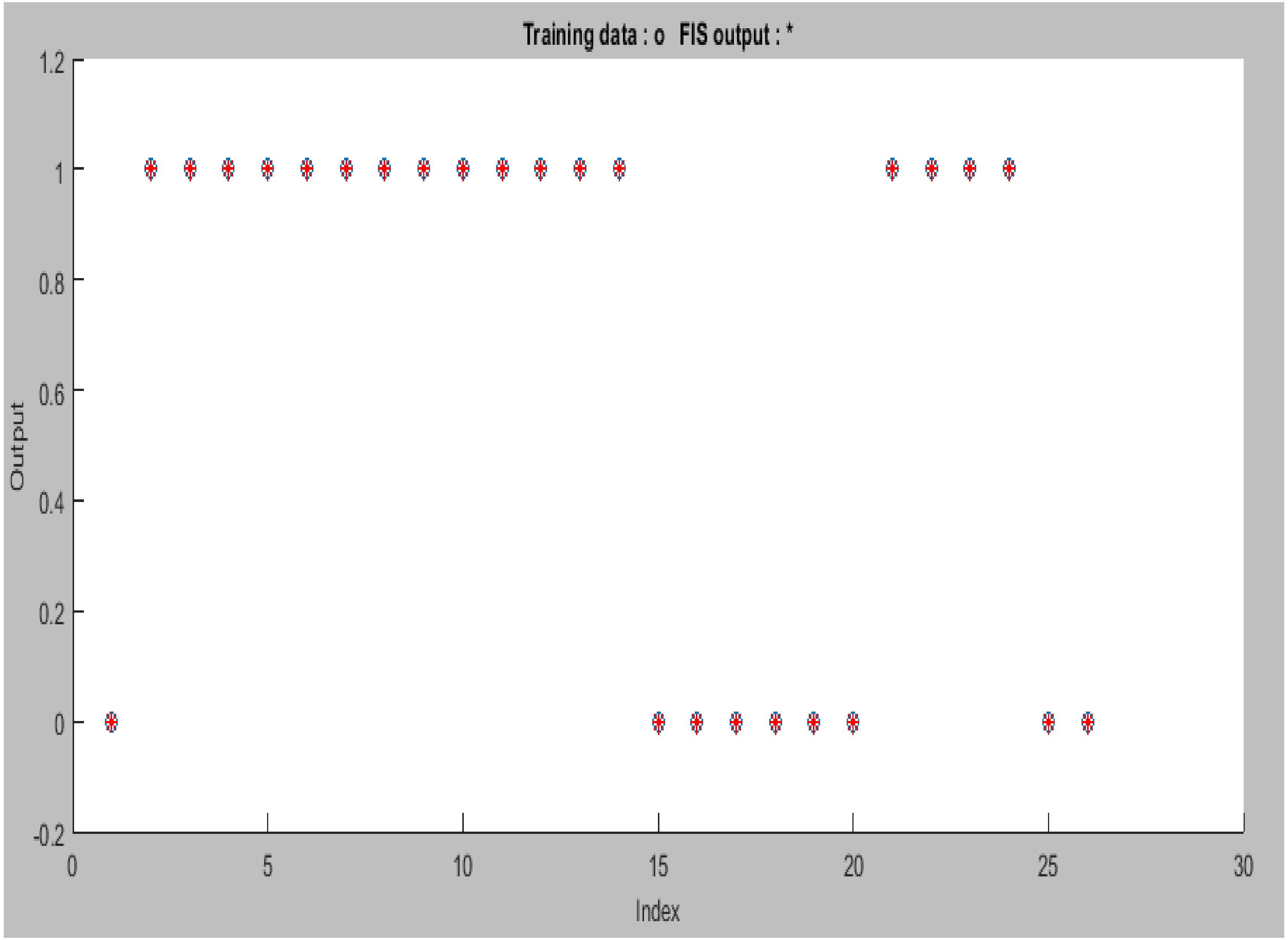
• Predicting socio-political events

- Socio-political data has been collected on the election results.
- We have used 26 songs from the hit list to check our model.
- The figure in the slide below shows the prediction (red star) of the election results in comparison with the historical data (blue circle).
- Along the y-axis 1 represents Labour Party and 0 represents Conservative Party winning the election, and along the x-axis the numbering of each hit song.
- The model predictions show good agreement with the historical data.



Comparison of the historical data (blue circle) and the model prediction (red star).

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- # Predicting socio-political events

- Along y-axis: 1 represents Labour Party and 0 represents Conservative Party winning the election
- Along x-axis: the hit songs.
- We see that the model predictions show good agreement with the historical data. Only a limited amount of data is available on the songs and more data would allow for more reliable prediction.

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Conclusions and future work

- A early stage socio-political events link with music is presented.
- Fuzzy neutral techniques is developed for predicting the link.
- Only a limited amount of data is available on the songs and more data would allow for more reliable prediction.
- Improving the model for political event prediction more sophisticated by adapting other machine learning techniques and using larger data sets.

Thank you!

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