Time series

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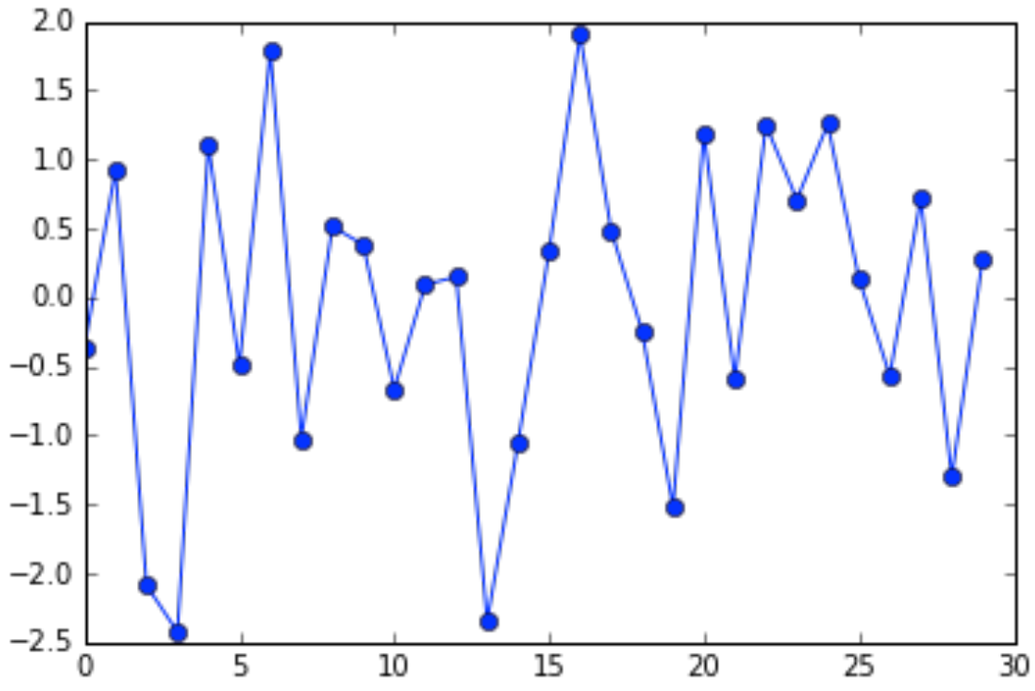
What is a Time Series

- you tell me….

http://www.rai.tv/dl/images/1324480933956bianconiglio1.jpg

What is a Time Series

- Sequence of points with timestamps i.e. an ORDERED collection of number



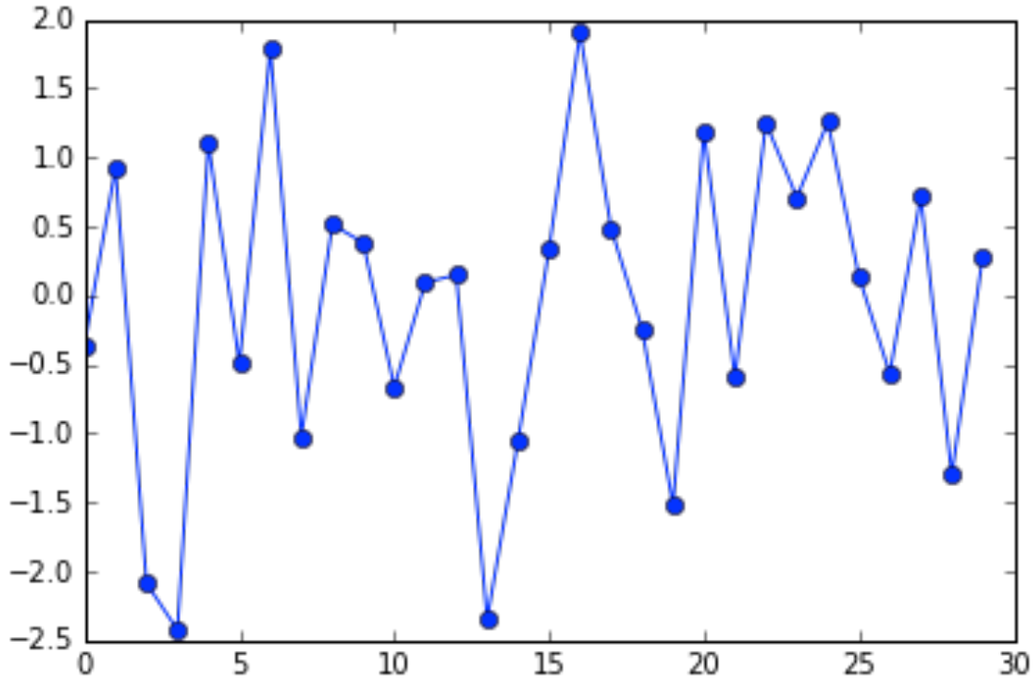
What is a Time Series

- Sequence of points with timestamps i.e. an ORDERED collection of number

- Timestamps could be

  - regular (sampling at fixed frequency)

  - irregular (events with associated timestamp)



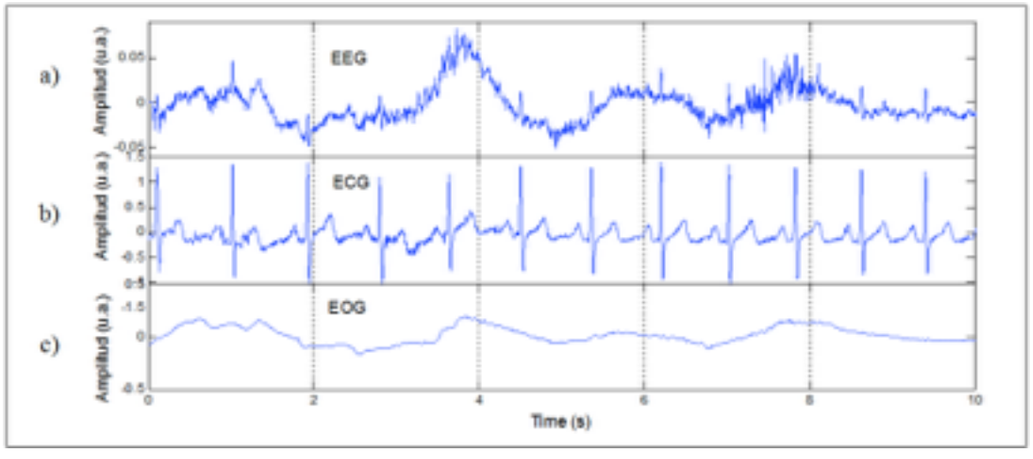
TSS are everywhere

- you tell me where….

TSS are everywhere

- Stock market
- Music
- Biosensors, biosignals (EEG, EKG, ECG, Wearables, etc…)
- Website monitoring and analytics
- IoT
- Energy Monitoring
- Traffic Signs
- Earthquakes
- Tides
- Sunspots
- …

http://projects-web.engr.colostate.edu/ece-sr-design/AY12/stocks/sim-030512.jpg



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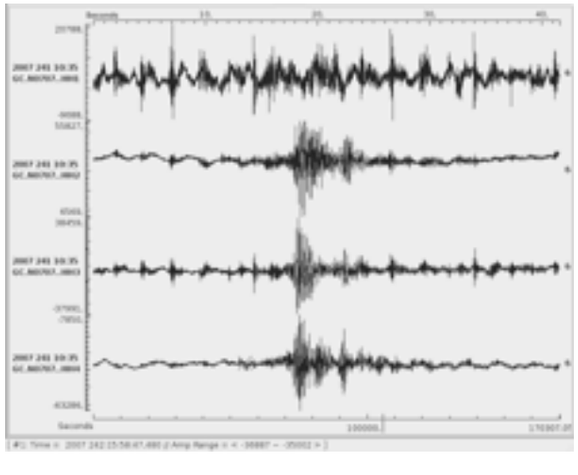
http://www.zipato.com/UserDocsImages/zipato_energy_monitoring.jpg



http://ricerca.ismar.cnr.it/CRUISE_REPORTS/2007/URANIA_NEAREST_2007/REPORT_NEAREST_2007_html_13a06b20.png

A time series DIFFERENT is…

http://i.huffpost.com/gen/805389/images/o-YODA-facebook.jpg

TSS are different from flat data

- you tell me why ….

	General government			Public non-financial corporations			Non-financial public sector		
	Receipts	Payments	Cash surplus	Receipts	Payments	Cash surplus	Receipts	Payments	Cash surplus
1987-88	32.6	32.4	0.2	4.0	5.9	-0.6	35.5	37.2	-0.4
1988-89	31.9	30.2	1.7	3.8	5.4	-0.1	34.8	34.6	1.6
1989-90	31.6	30.4	1.2	3.7	6.7	-1.6	34.1	36.0	-0.4
1990-91	31.6	32.1	-0.6	3.8	5.9	-0.7	34.2	36.8	-1.2
1991-92	30.3	34.1	-3.9	3.6	5.4	0.0	32.5	36.2	-3.8
1992-93	29.8	34.4	-4.7	3.6	5.0	0.3	32.0	38.1	-4.3
1993-94	30.6	34.5	-3.9	3.8	4.3	0.9	32.7	37.3	-3.0
1994-95	31.4	34.1	-2.7	3.4	4.5	0.8	33.3	37.2	-2.0
1995-96	32.6	34.0	-1.4	3.0	4.5	0.1	33.9	36.9	-1.4
1996-97	33.5	33.9	-0.4	3.1	4.2	0.3	34.4	35.9	-0.1
1997-98	33.1	32.6	0.5	3.0	3.7	0.6	34.4	34.7	1.1
1998-99	37.9	37.4	0.4	na	na	-0.6	na	na	-0.5
1999-00	38.8	36.3	2.5	na	na	-0.1	na	na	2.4
2000-01	37.8	36.5	1.3	na	na	0.0	na	na	1.3
2001-02	36.4	35.9	0.6	na	na	0.1	na	na	0.6
2002-03	37.8	36.3	1.6	na	na	-0.1	na	na	1.6
2003-04(e)	37.3	36.4	0.8	na	na	-0.3	na	na	0.5
2004-05(e)	36.5	35.9	0.6	na	na	na	na	na	na
2005-06(p)	35.9	35.4	0.5	na	na	na	na	na	na
2006-07(p)	35.6	34.8	0.7	na	na	na	na	na	na

http://www.budget.gov.au/2004-05/bp1/image/bst12-19.gif

	A	B	D	G	H
1	Ph #	Ph Nam	Height	M Wt	B Wt
2	123	Smith	150	60.3	3.4
3	123	Smith		62.3	3.7
4	123	Smith	64	58.7	2.9
5	123	Smith	649	57.9	3.1
6	123	Smith	649308	55.2	1.4
7	123	Smith	2384	61.8	2.5
8	123	Smith	23	64.1	2.7
9	220	Jones		59.2	2.2
10	220	Jones	17	57.4	3.6
11	220	Jones	177	58.2	3.4
12				59.51	2.89

http://audilab.bmed.mcgill.ca/~funnell/Bacon/DBMS/flat.gif

TSS are different

- Ordered events

http://thumbs.dreamstime.com/t/past-now-future-notes-arrow-blackboard-45598002.jpg

TSS are different

- Ordered events
- Correlation in Time

http://thumbs.dreamstime.com/t/past-now-future-notes-arrow-blackboard-45598002.jpg

TSS are different

- Ordered events
- Correlation in Time
- Periodicity

http://thumbs.dreamstime.com/t/past-now-future-notes-arrow-blackboard-45598002.jpg

TSS are different

- Ordered events
- Correlation in Time
- Periodicity
- Past …. Future …

http://thumbs.dreamstime.com/t/past-now-future-notes-arrow-blackboard-45598002.jpg

TSS are different

- Ordered events
- Correlation in Time
- Periodicity
- Past …. Future …

http://thumbs.dreamstime.com/t/past-now-future-notes-arrow-blackboard-45598002.jpg

=> ML with TSS is different

Machine Learning with Time Series Learn you will….

http://i.huffpost.com/gen/805389/images/o-YODA-facebook.jpg

ML with TSS

- Example of problems …

ML with TSS

- Prediction of future values (regression)
- Pattern recognition & segmentation (classification, clustering, anomaly detection, dim reduction)
- Compression, noise reduction (preprocessing)

Prediction

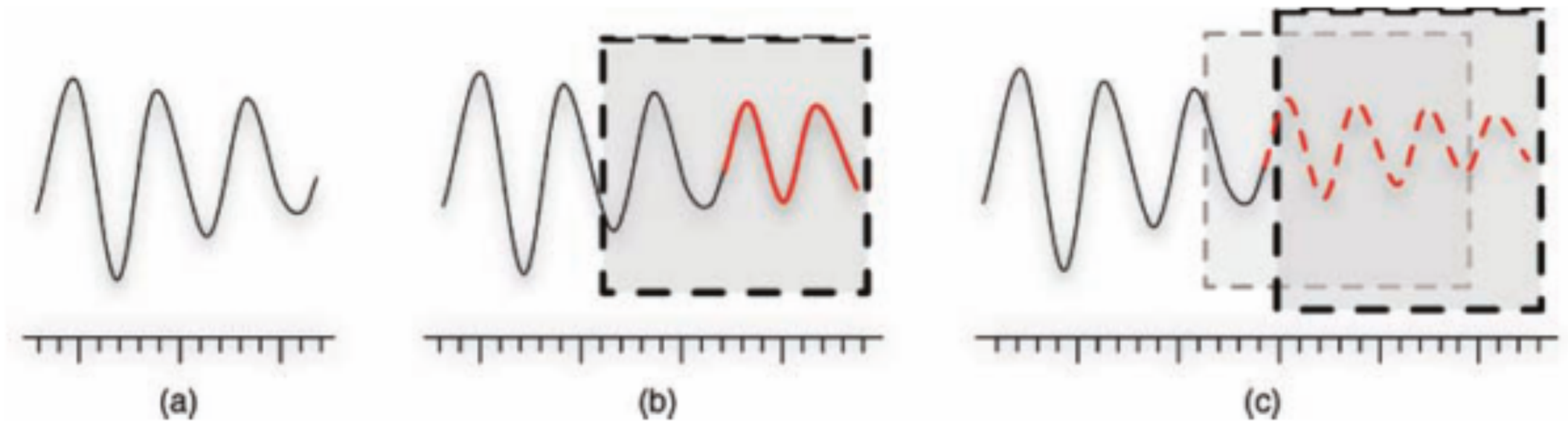


Fig. 5. A typical example of the time-series prediction task. (a) The input time series may exhibit a periodical and thus predictable structure. (b) The goal is to forecast a maximum number of upcoming datapoints within a prediction window. (c) The task becomes really hard when it comes to having *recursive prediction*, that is, the long-term prediction of a time series implies reusing the earlier forecast values as inputs in order to go on predicting.

http://dl.acm.org/citation.cfm?doid=2379776.2379788

Anomaly detection

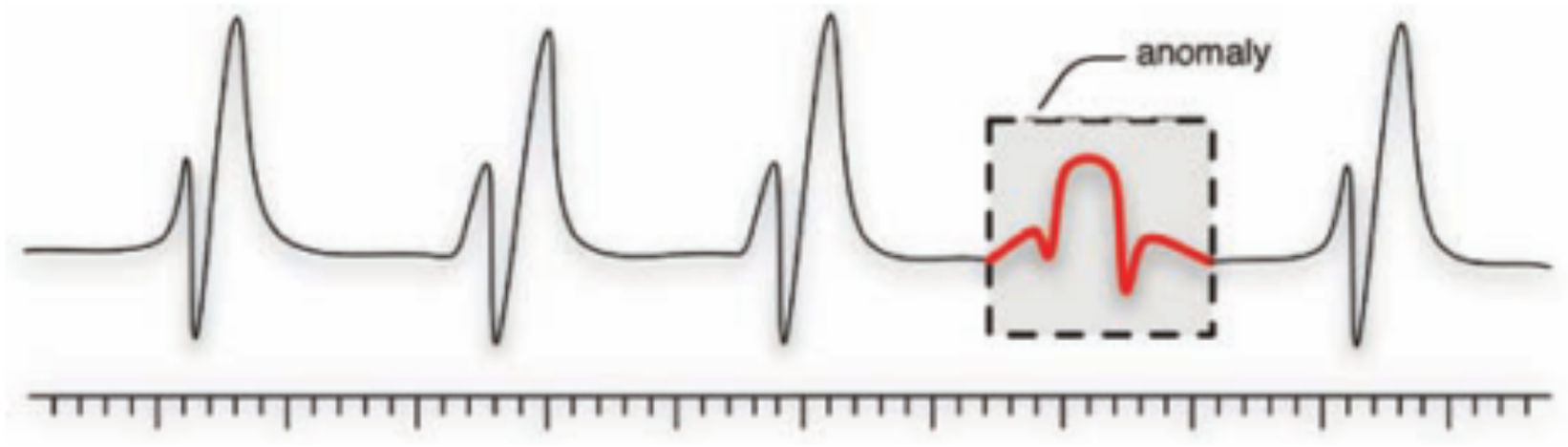


Fig. 6. An idealized example of the anomaly detection task. A long time series which exhibits some kind of periodical structure can be modeled thanks to a reduced pattern of "standard" behavior. The goal is thus to find subsequences that do not follow the model and may therefore be considered as anomalies.

http://dl.acm.org/citation.cfm?doid=2379776.2379788

Segmentation

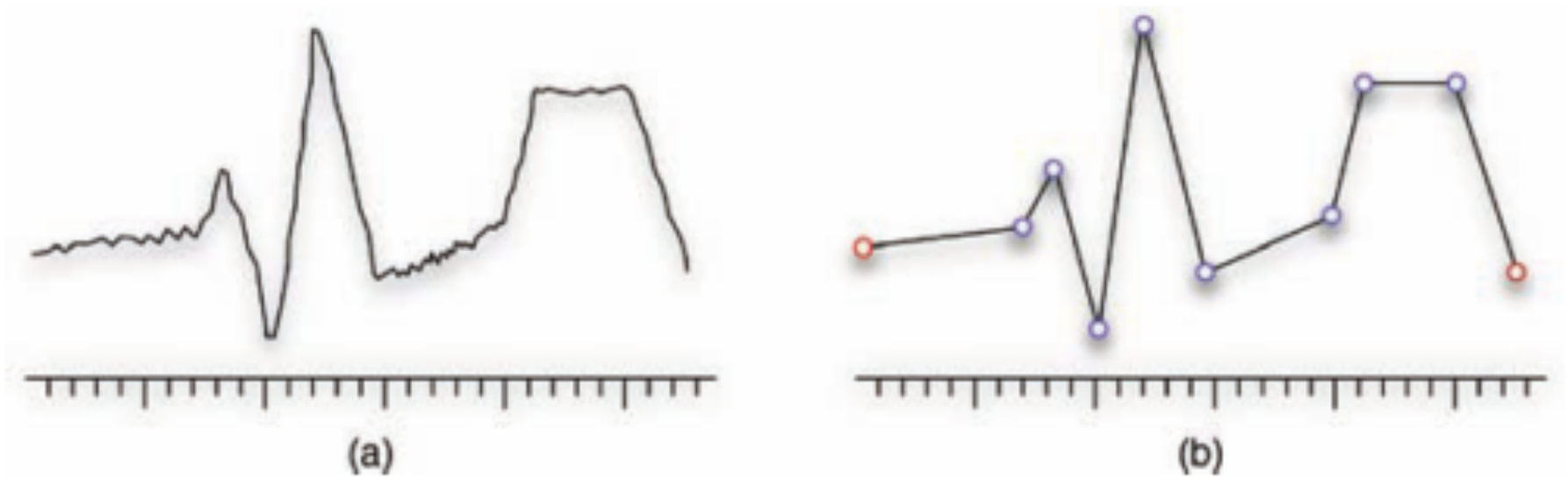


Fig. 4. Example of application of a segmentation system. From (a) usually noisy time series containing a very large number of datapoints, the goal is to find (b) the closest approximation of the input time series with the maximal dimensionality reduction factor without losing any of its essential features.

http://dl.acm.org/citation.cfm?doid=2379776.2379788

Motif Discovery

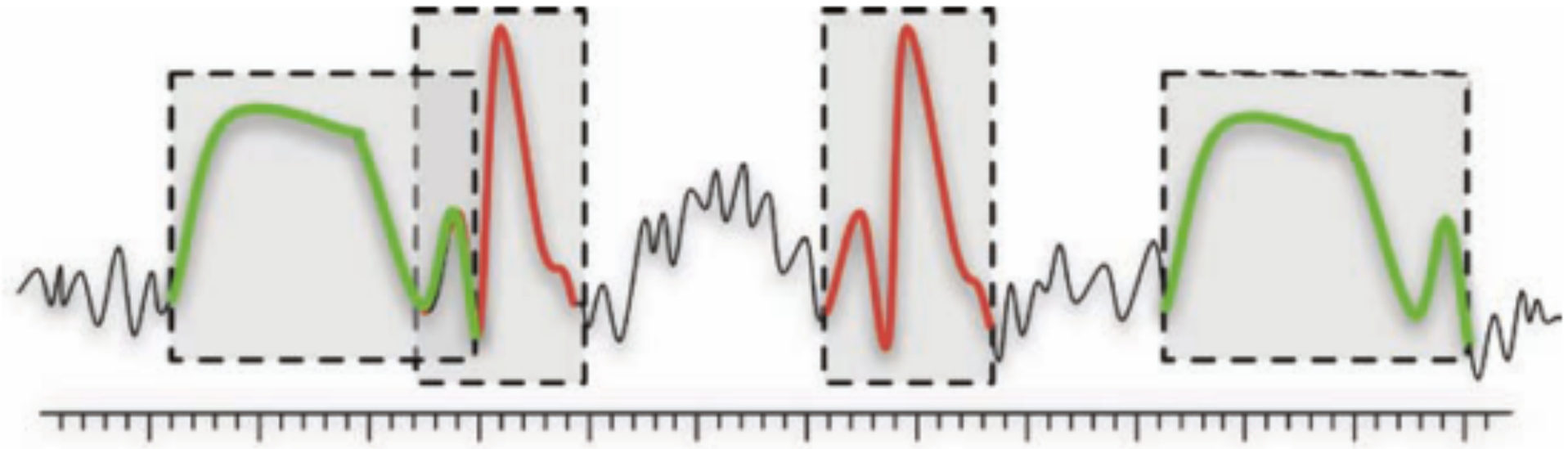


Fig. 7. The task of motif discovery consists in finding every subsequence that appears recurrently in a longer time series. These subsequences are named motifs. This task exhibits a high combinatorial complexity as several motifs can exist within a single series, motifs can be of various lengths, and even overlap.

http://dl.acm.org/citation.cfm?doid=2379776.2379788

ML Pipeline

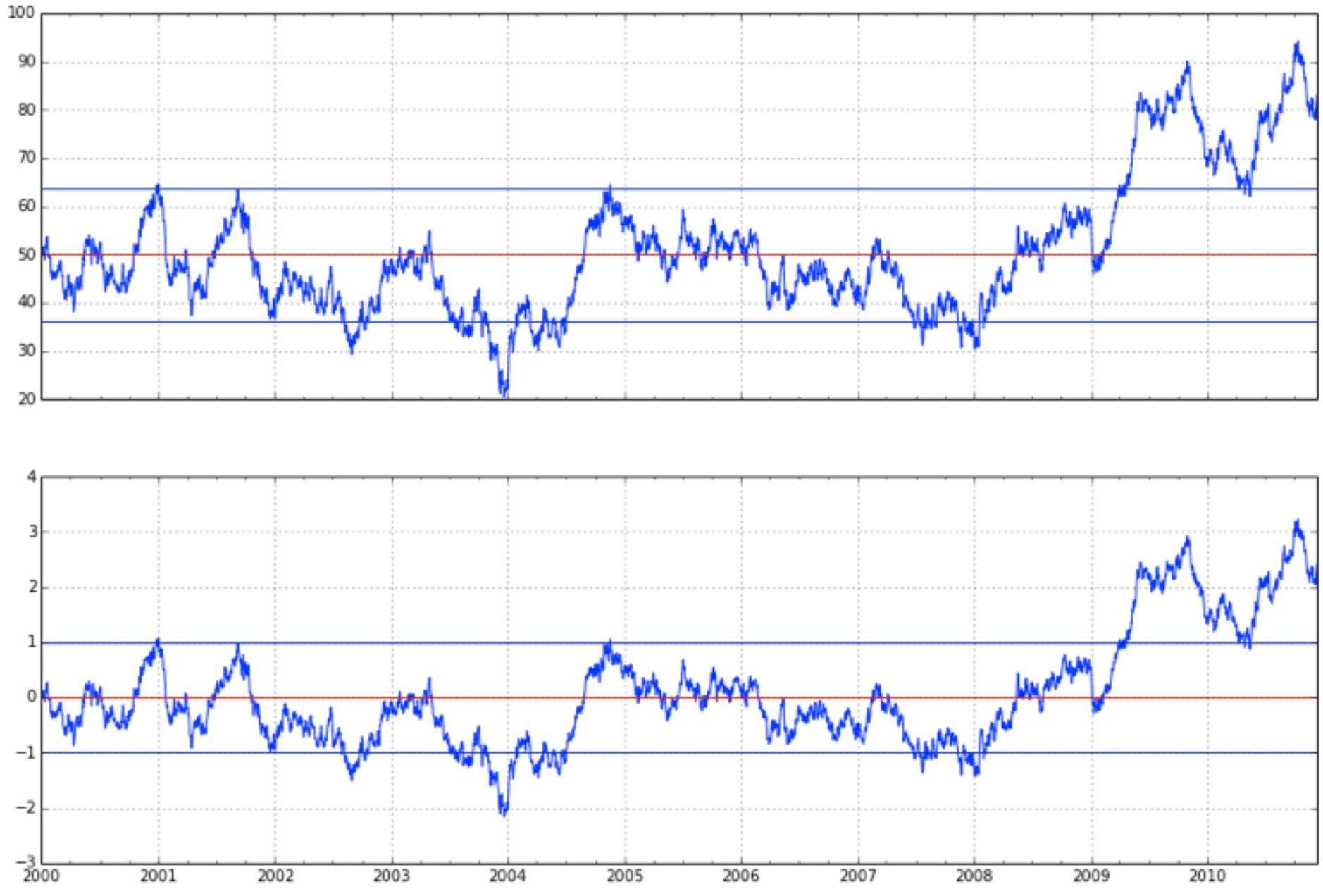
- Data Munging, preprocessing
- Feature Extraction, feature engineering
- Model Building and Validation
- Results visualization

Preprocessing

- Normalization
- Filtering

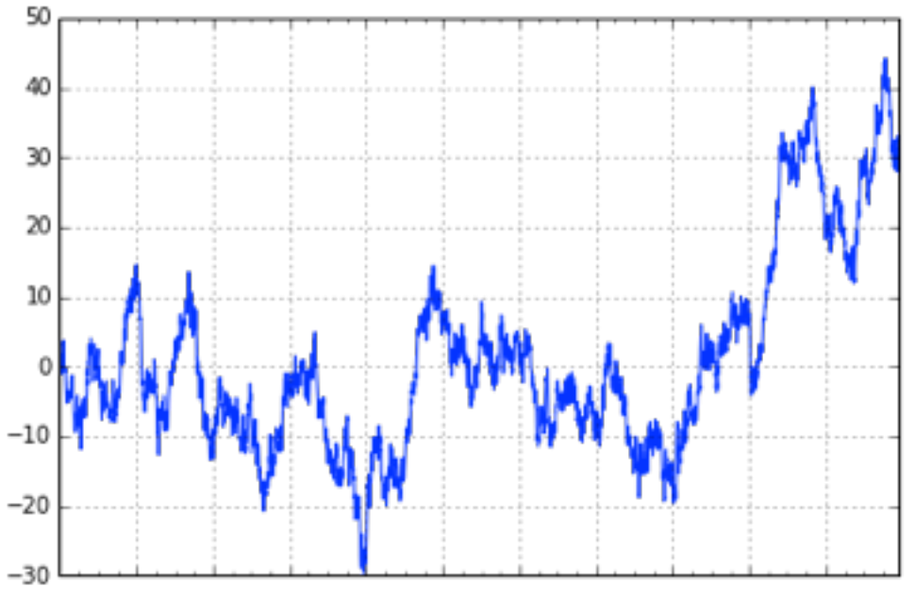
Let’s normalize ‘em TSS

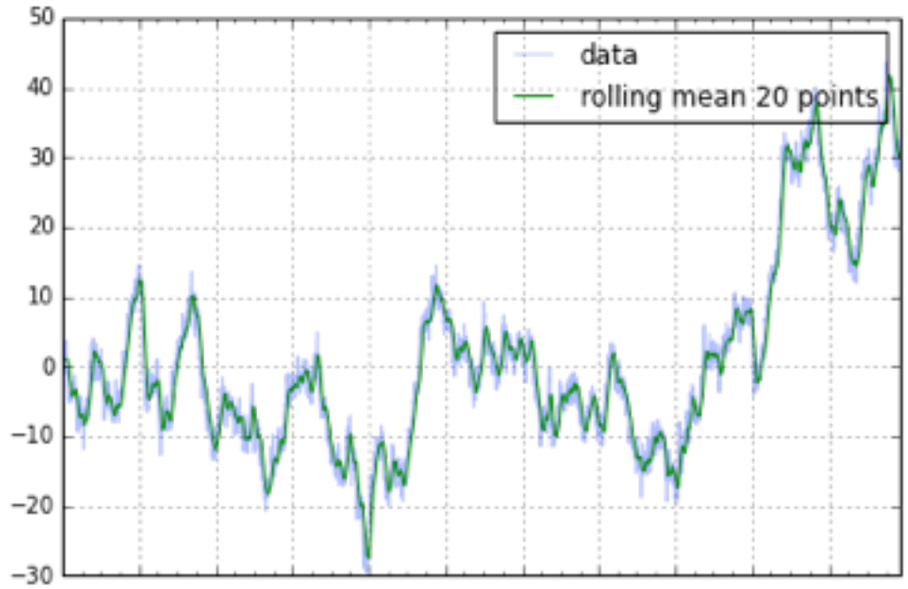
Preprocessing: normalization

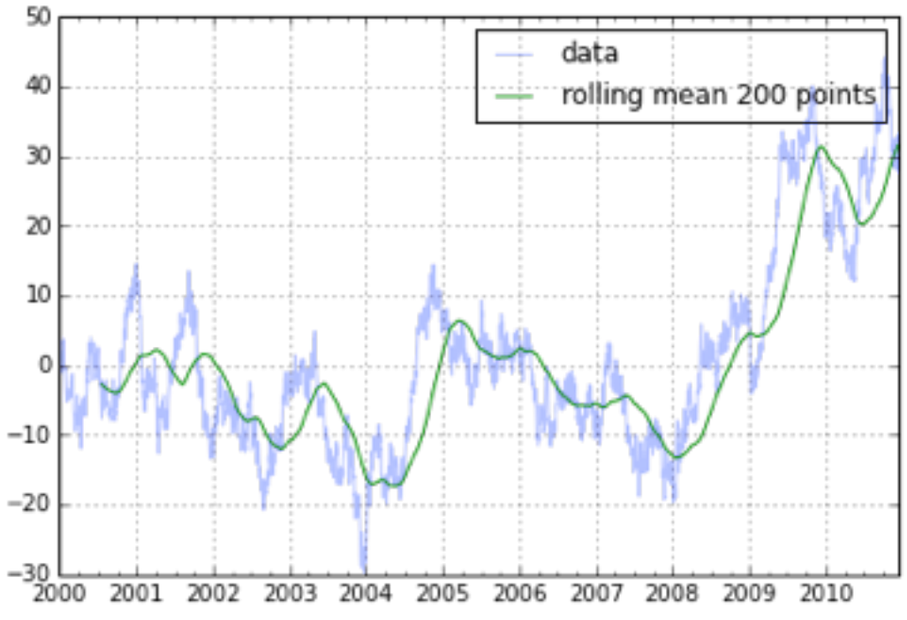


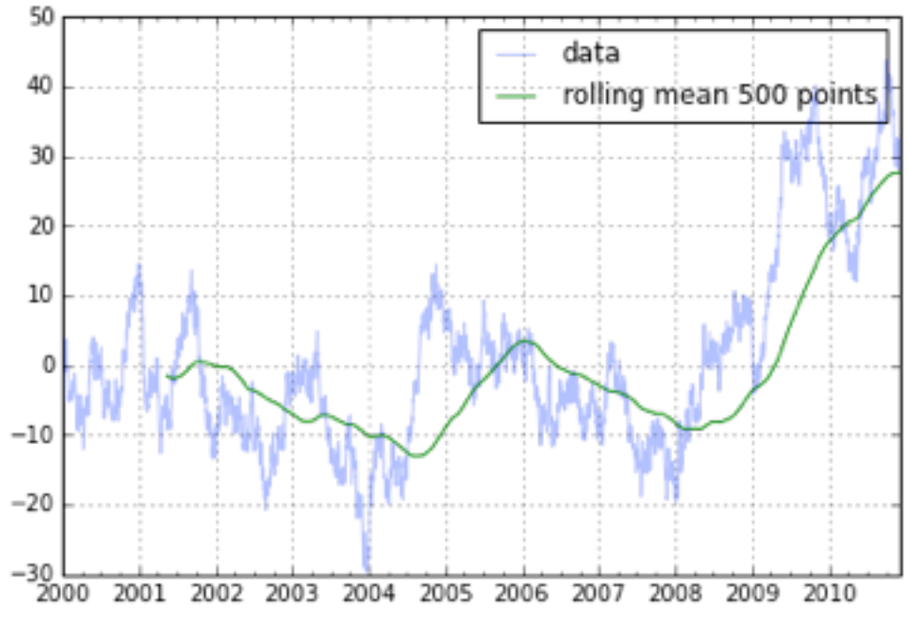
http://lovebeingretired.com/wp-content/uploads/2013/03/Child-covering-ears-against-loud-noise.jpg

Preprocessing: noise reduction

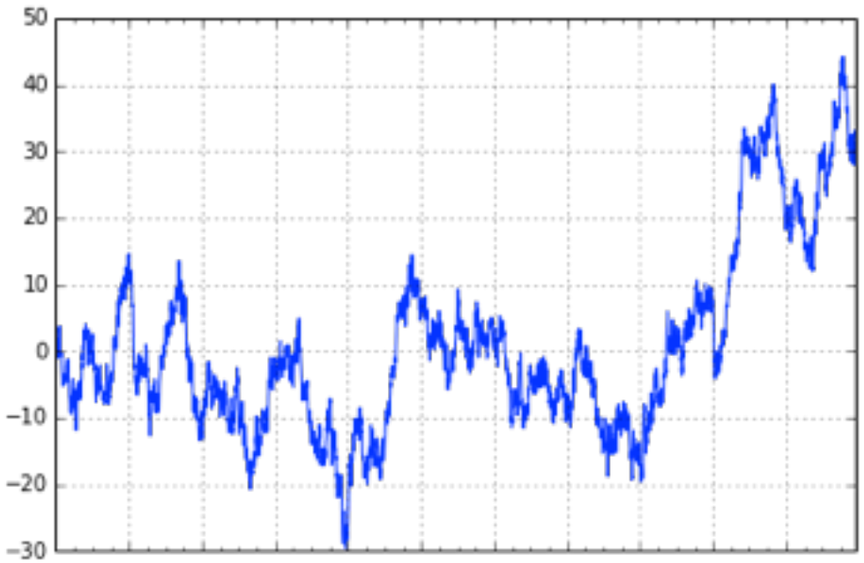


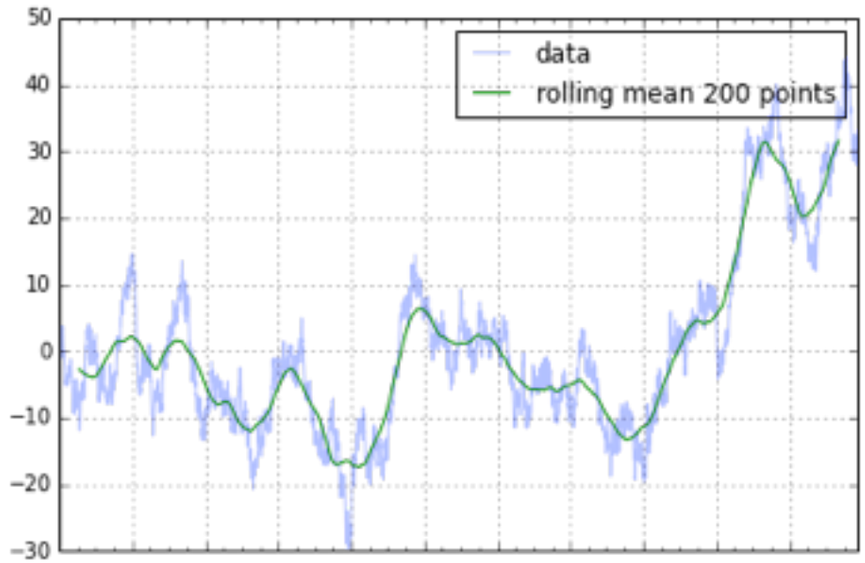


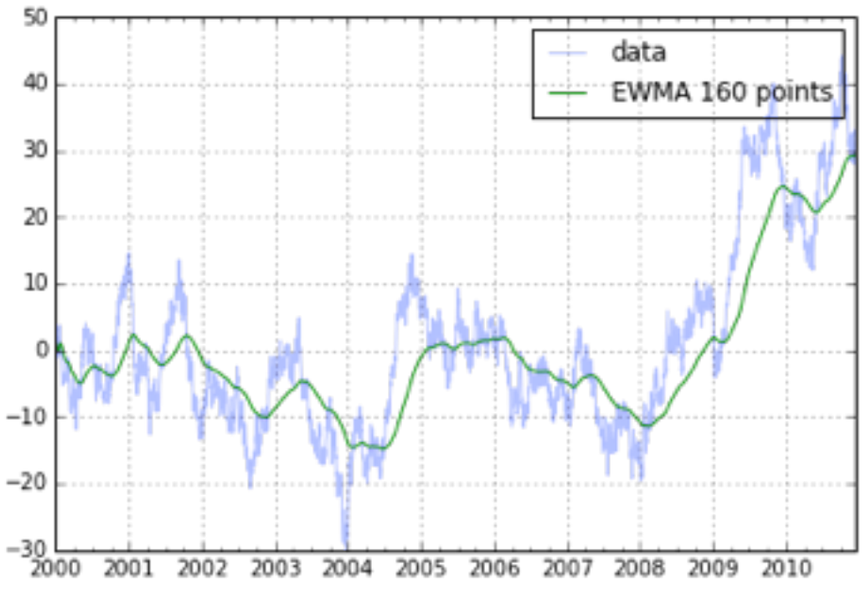


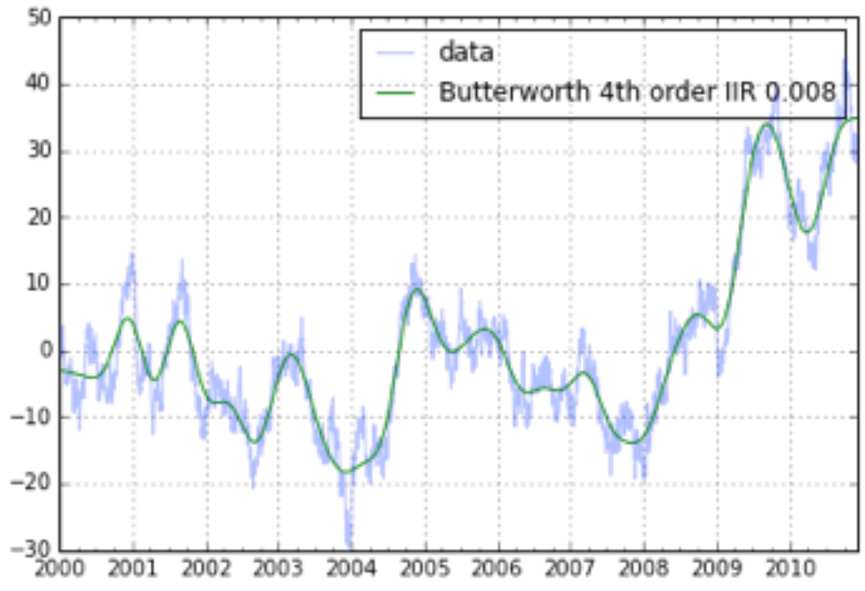


Preprocessing: noise reduction









Feature Extraction

- Raw data
- Differences
- Rolling windows

Feature Extraction

http://thumbs.dreamstime.com/z/miner-gold-14017924.jpg

Feature Extraction

https://encrypted-tbn1.gstatic.com/images?q=tbn:ANd9GcQVwGtUZNpPs4f6aoFOuURLYHnB95TiiY9QfyrMig3IBfwmbbEH

Features: raw data

$$X = \begin{bmatrix} y_{N-1} & y_{N-2} & \cdots & y_{N-n-1} \\ y_{N-2} & y_{N-3} & \cdots & y_{N-n-2} \\ \vdots & \vdots & \vdots & \vdots \\ y_n & y_{n-1} & \cdots & y_1 \end{bmatrix}$$

$$Y = \begin{bmatrix} y_N \\ y_{N-1} \\ \vdots \\ y_{n+1} \end{bmatrix}$$

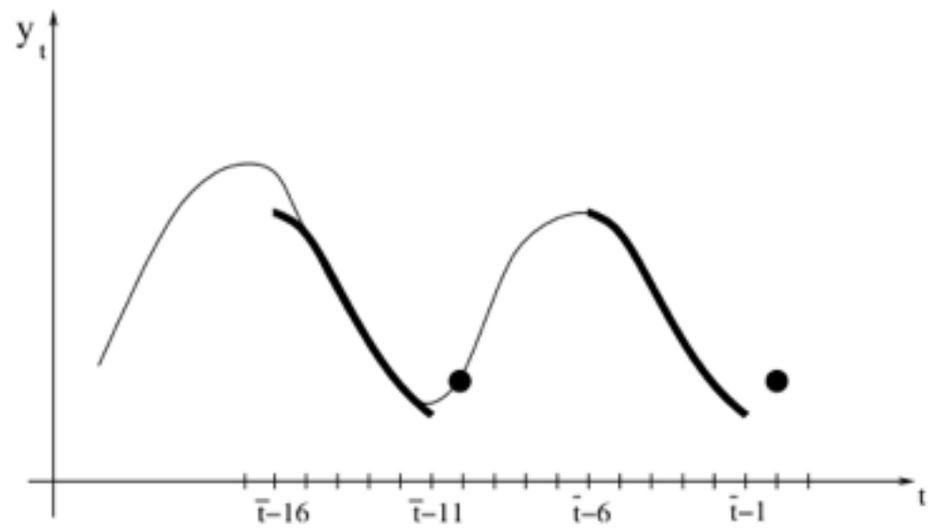


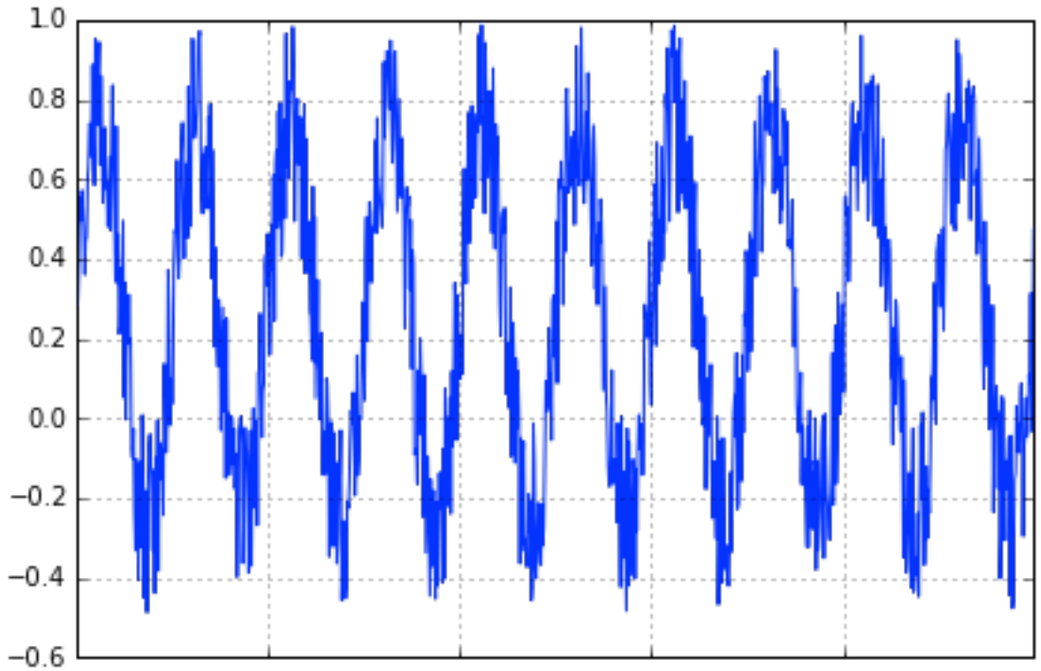
Fig. 2. Nearest-neighbor one-step-ahead forecasts. We want to predict at time $\bar{t}-1$ the next value of the series y of order $n=6$. The pattern $y_{\bar{t}-16}, y_{\bar{t}-15}, \ldots, y_{\bar{t}-11}$ is the most similar to the pattern $\{y_{\bar{t}-6}, y_{\bar{t}-5}, \ldots, y_{\bar{t}-1}\}$. Then, the prediction $\hat{y}_{\bar{t}} = y_{\bar{t}-10}$ is returned.

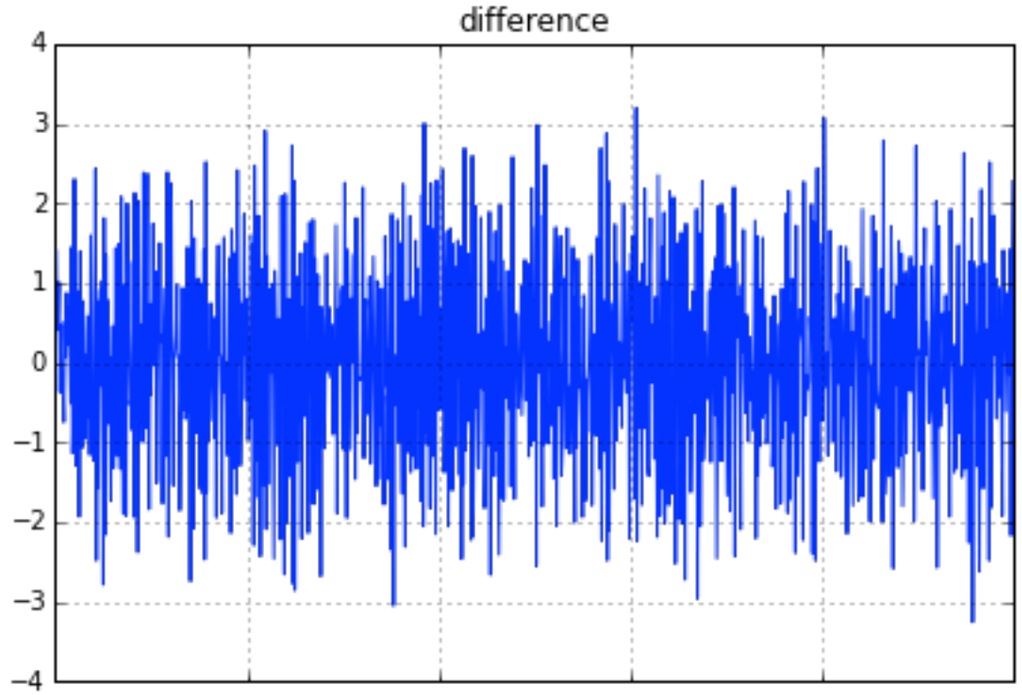
http://link.springer.com/chapter/10.1007/978-3-642-36318-4_3

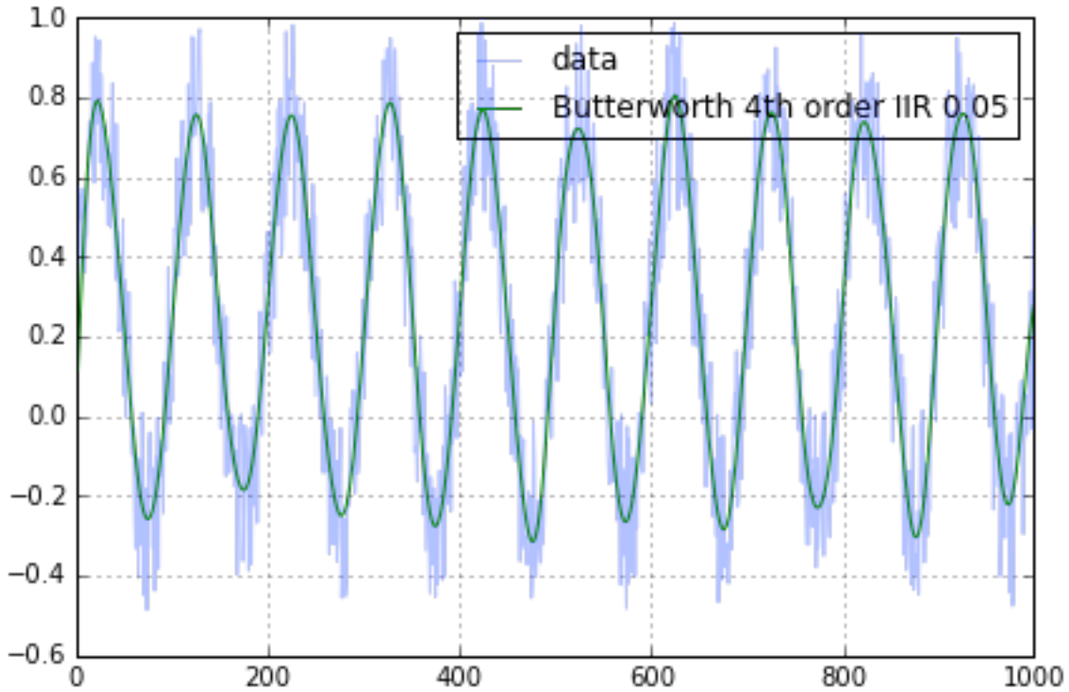
Features: differences

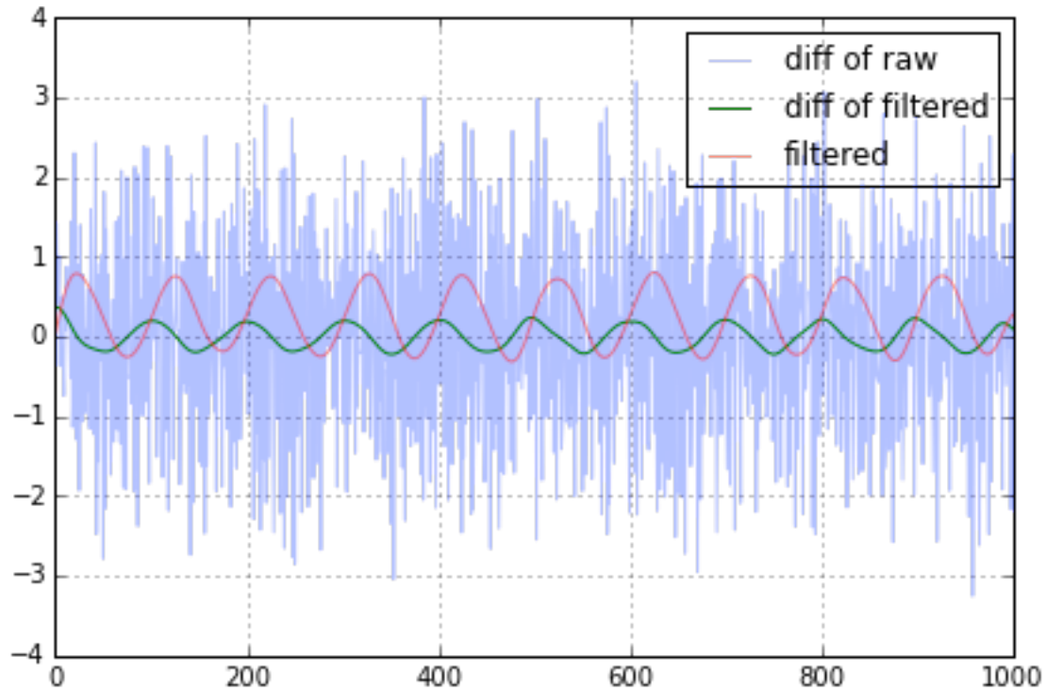
- diff(t) = {t[i] - t[i-1]} for i = 1…..N

Features: differences

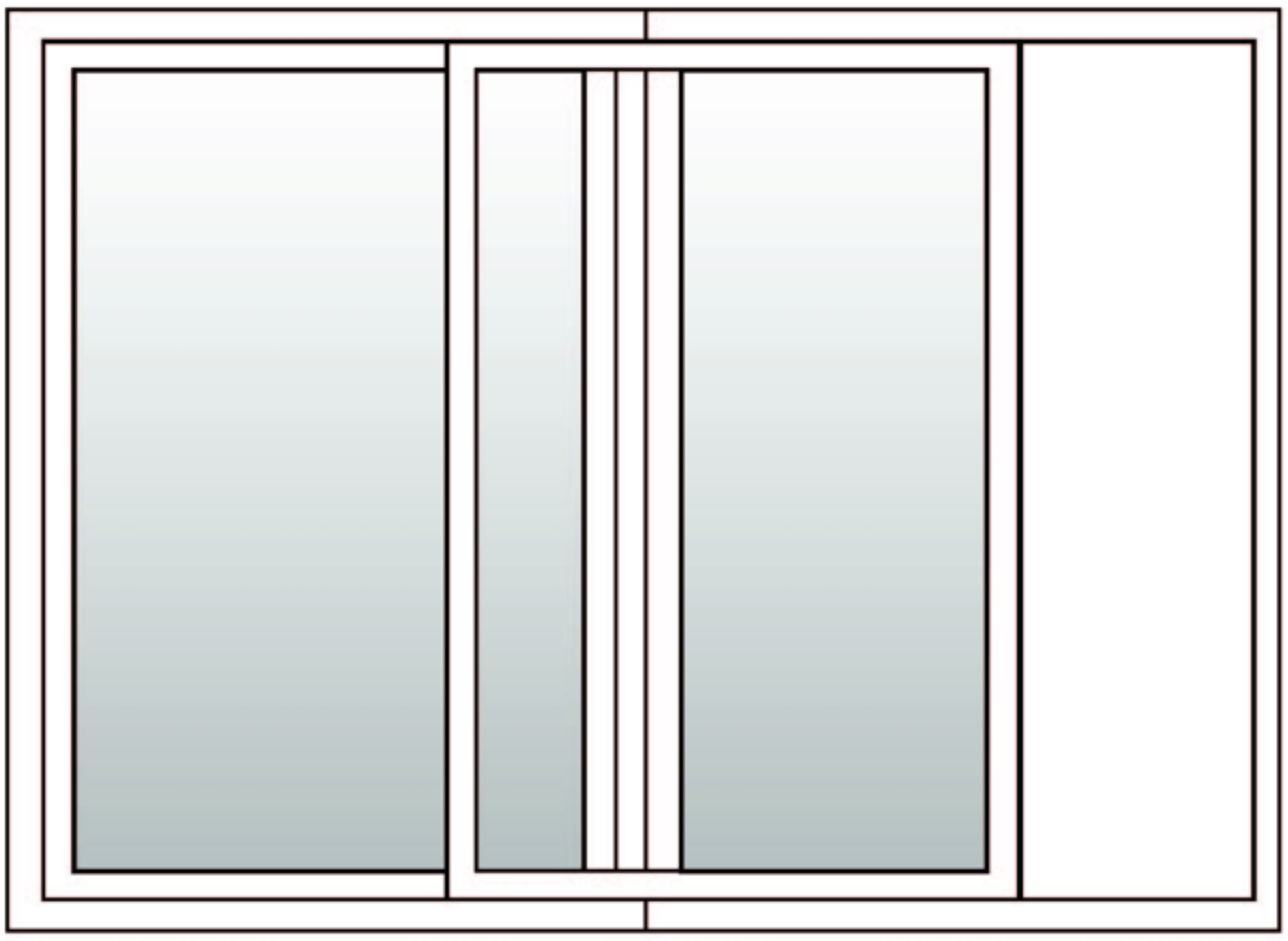






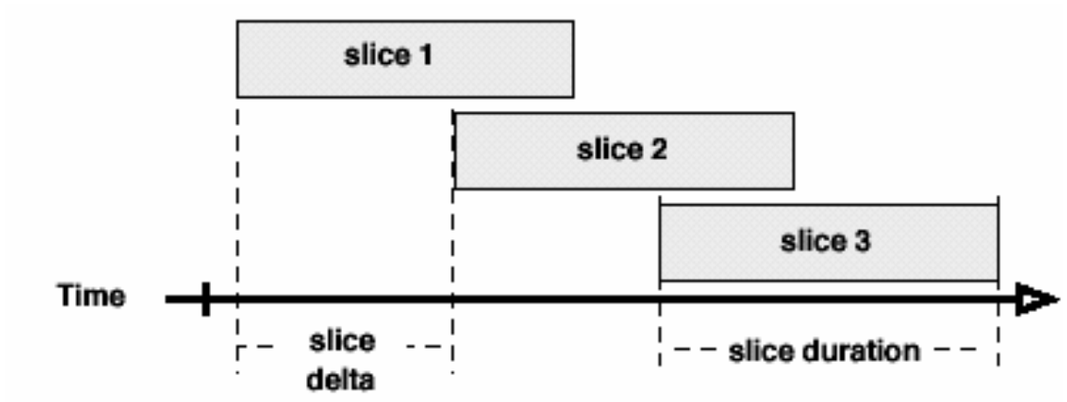


Rolling Windows



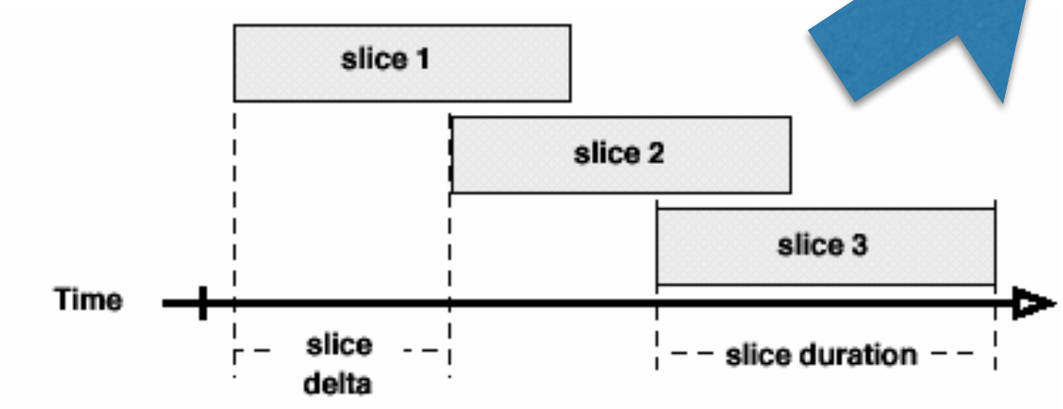
http://www.taylorraeconstruction.com/sites/default/files/Slider2Panel.jpg

Rolling Windows



http://www.cmu.edu/joss/content/articles/volume7/deMollMcFarland/images/F5_timeSlice.gif

Rolling Windows



- For each window calculate features:
  - Stats: Mean, Stdev, Moments
  - Frequency: Spectral Band Power, Entropy
  - Autoregressive model parameters
  - FFT, Hjorth, Mann-Kendall …
  - Correlation dimension, integral, density, entropy
  - etc….

http://www.cmu.edu/joss/content/articles/volume7/deMollMcFarland/images/F5_timeSlice.gif

http://en.wikipedia.org/wiki/Time_series

More complex windows

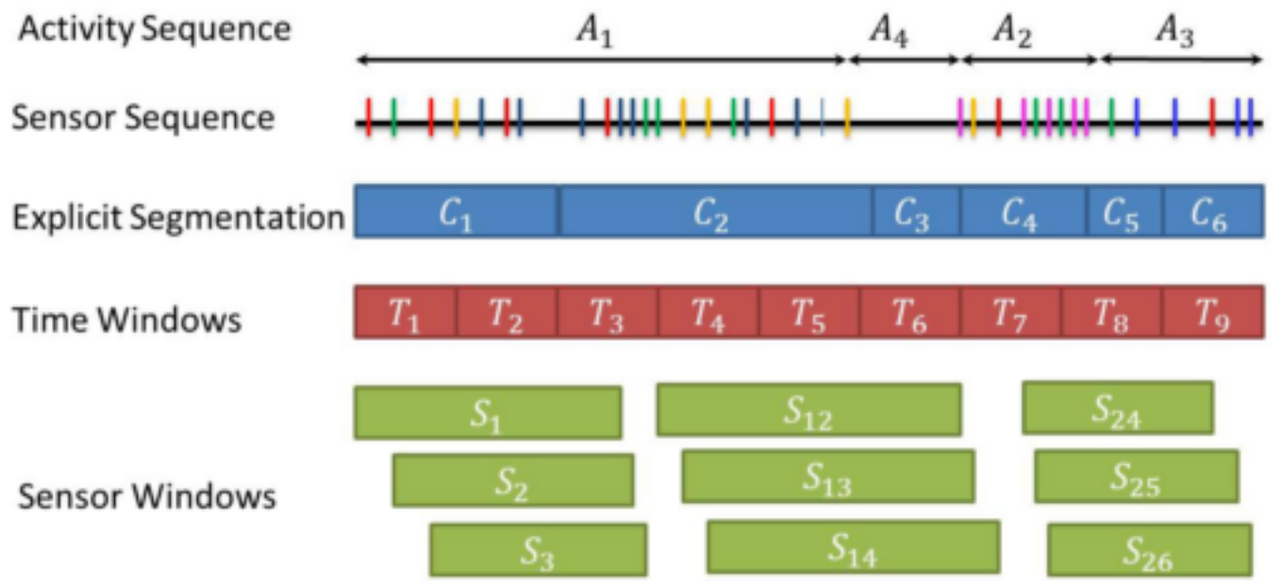


Figure 1: Illustration of the different approaches for stream processing. The different motion/door sensor firings are depicted by the colored vertical lines. The sensor windows are obtained using a sliding window of length 10 sensor events.

http://www.researchgate.net/publication/261610842_Activity_Recognition_on_Streaming_Sensor_Data

Complete Pipeline

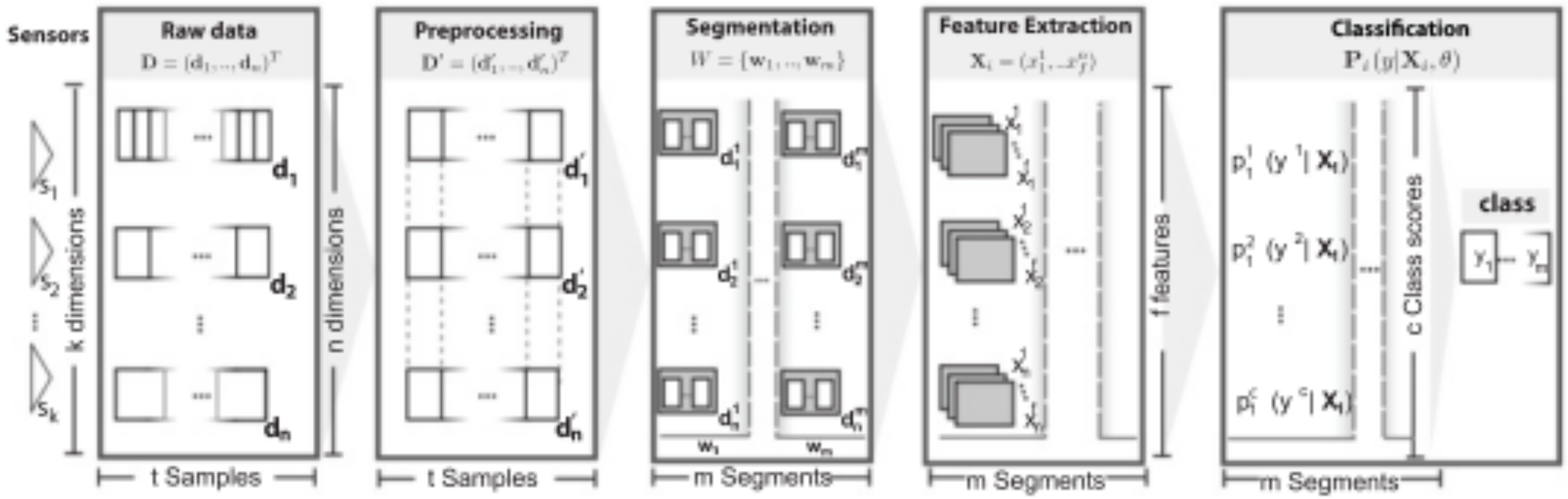


Fig. 1. Typical Activity Recognition Chain (ARC) to recognize activities from wearable sensors. An ARC comprises stages for data acquisition, signal preprocessing and segmentation, feature extraction and selection, training, and classification. Raw signals ($\mathbf{D}$) are first processed ($\mathbf{D}'$) and split into m segments ($\mathbf{W_i}$) from which feature vectors ($\mathbf{X_i}$) are extracted. Given features ($\mathbf{X_i}$), a model with parameters θ scores c activity classes $\mathbf{Y_i} = \{y^1, \ldots, y^c\}$ with a confidence vector $\mathbf{p}_i$.

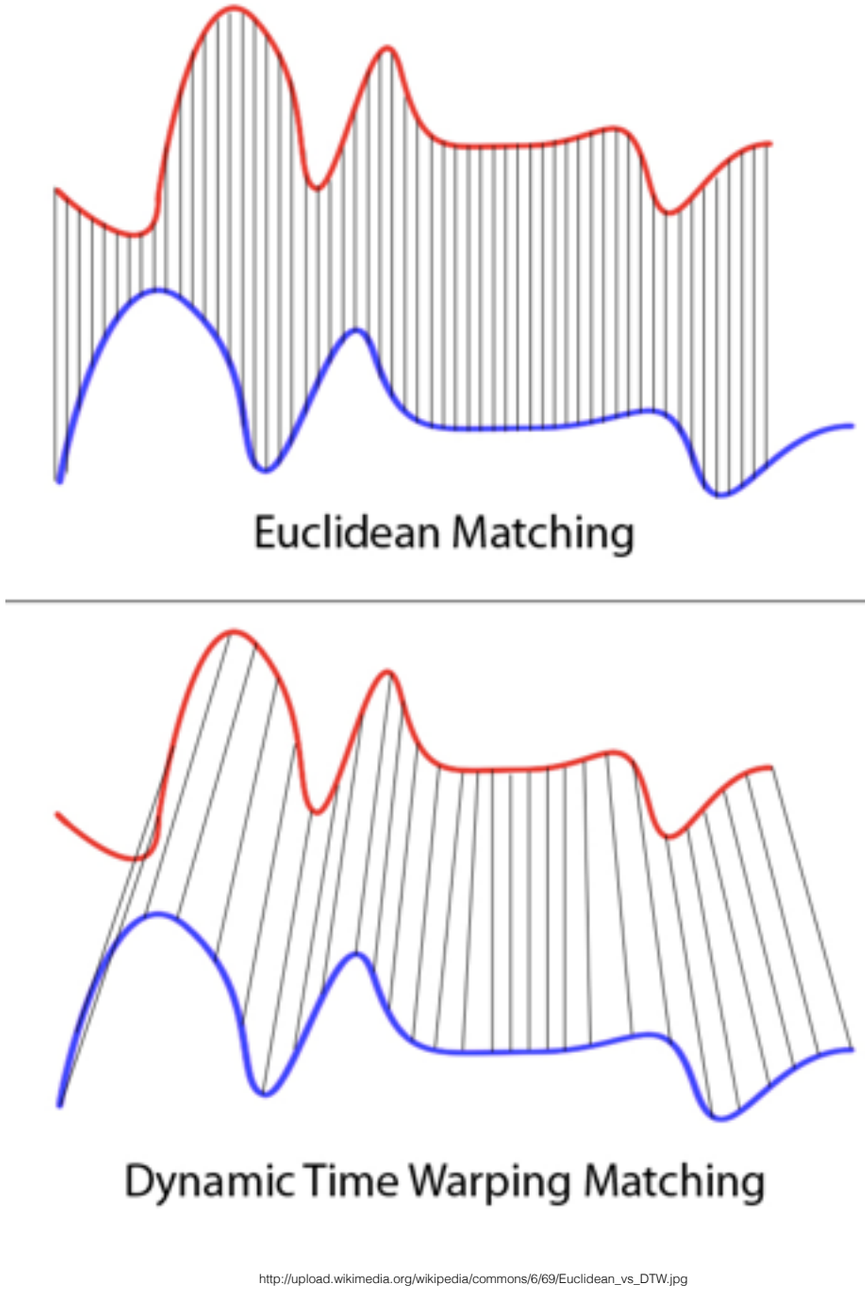
http://dl.acm.org/citation.cfm?id=2499621

Similarity Between TSS

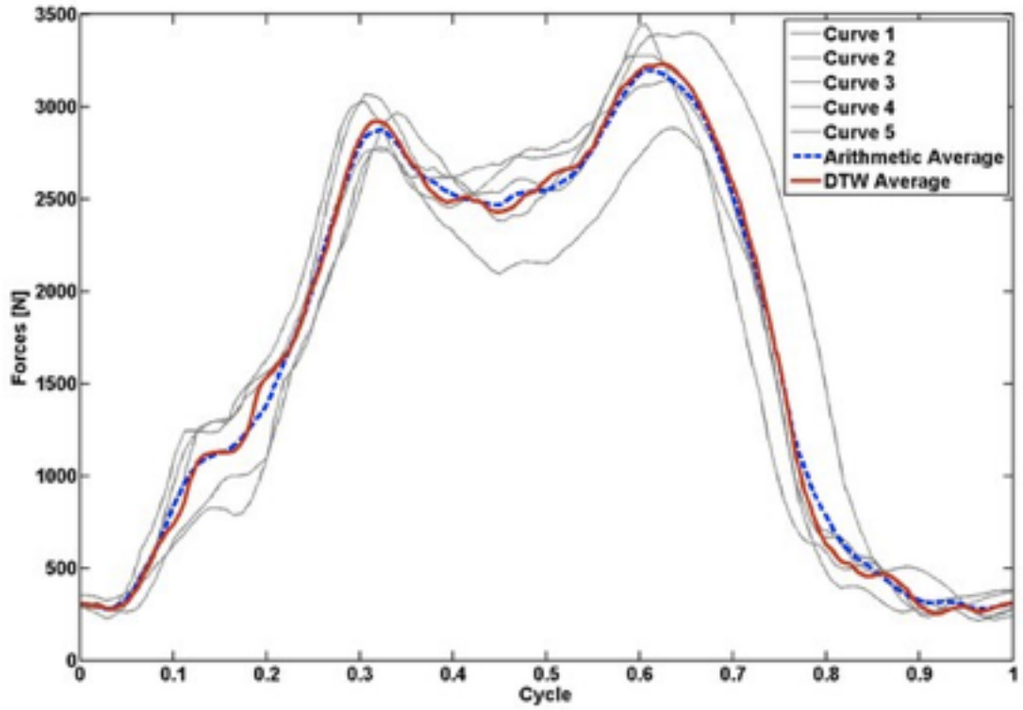
http://www.cossurgery.com.au/wp-content/uploads/2012/10/Twins.jpg

http://www.cossurgery.com.au/wp-content/uploads/2012/10/Twins.jpg

Similarity Between TSS



http://upload.wikimedia.org/wikipedia/commons/6/69/Euclidean_vs_DTW.jpg



http://www.orthoload.com/wp-content/uploads/206_6.jpg

Distance Measures

Table I. Comparison of the Distance Measures surveyed in This Article with the Four Properties of Robustness

Distance measure	Scale	Warp	Noise	Outliers	Metric	Cost	Param
Shape-based							
L_p norms					√	$O(n)$	0
Dynamic Time Warping (DTW)		√				$O(n^2)$	1
LB_Keogh (DTW)		√	√		√	$O(n)$	1
Spatial Assembling (SpADe)	√	√	√			$O(n^2)$	4
Optimal Bijection (OSB)		√	√	√		$O(n^2)$	2
DISSIM		√	√		√	$O(n^2)$	0
Edit-based							
Levenshtein				√	√	$O(n^2)$	0
Weighted Levenshtein				√	√	$O(n^2)$	3
Edit with Real Penalty (ERP)		√		√	√	$O(n^2)$	2
Time Warp Edit Distance (TWED)		√		√	√	$O(n^2)$	2
Longest Common SubSeq (LCSS)		√	√	√		$O(n)$	2
Sequence Weighted Align (Swale)		√	√	√		$O(n)$	3
Edit Distance on Real (EDR)		√	√	√	√	$O(n^2)$	2
Extended Edit Distance (EED)		√	√	√	√	$O(n^2)$	1
Constraint Continuous Edit (CCED)		√	√	√		$O(n)$	1
Feature-based							
Likelihood			√	√	√	$O(n)$	0
Autocorrelation			√	√	√	$O(nlogn)$	0
Vector quantization		√	√	√	√	$O(n^2)$	2
Threshold Queries (TQuest)		√	√	√		$O(n^2logn)$	1
Random Vectors		√	√	√		$O(n)$	1
Histogram			√	√	√	$O(n)$	0
WARP	√	√	√		√	$O(n^2)$	0
Structure-based							
Model-based							
Markov Chain (MC)			√	√		$O(n)$	0
Hidden Markov Models (HMM)	√	√	√	√		$O(n^2)$	1
Auto-Regressive (ARMA)			√	√		$O(n^2)$	2
Kullback-Leibler			√	√	√	$O(n)$	0
Compression-based							
Compression Dissimilarity (CDM)		√	√	√		$O(n)$	0
Parsing-based		√	√	√		$O(n)$	0

Each distance measure is thus distinguished as *scale* (amplitude), *warp* (time), *noise* or *outliers* robust. The next column shows whether the proposed distance is a metric. The cost is given as a simplified factor of computational complexity. The last column gives the minimum number of parameters setting required by the distance measure.

http://dl.acm.org/citation.cfm?doid=2379776.2379788

Subsequence clustering

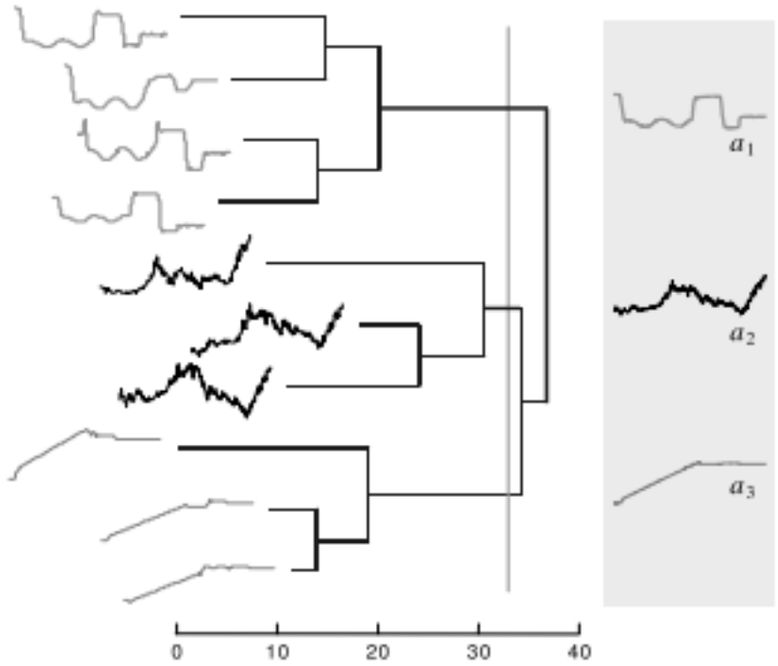


Figure 3. A hierarchical clustering of ten time series. The clustering can be converted to a k partitional clustering by "sliding" a cutting line until it intersects k lines of the dendrograms, then averaging the time series in the k subtrees to form k cluster centers (gray panel).

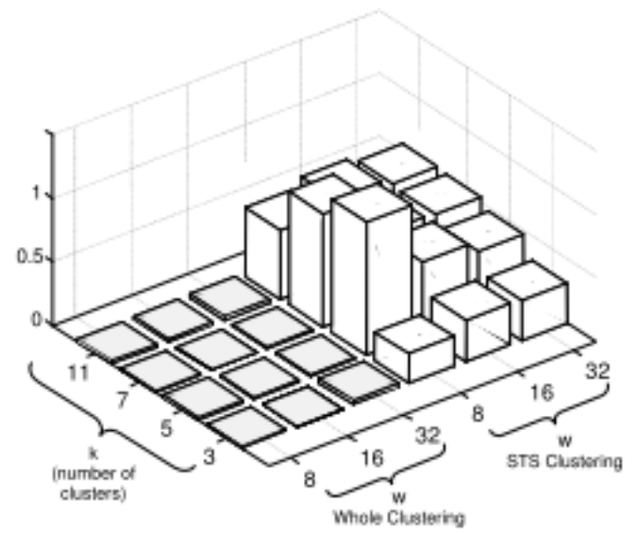


Figure 6. A comparison of the clustering meaningfulness for whole clustering, and STS clustering, using k-means with a variety of parameters. The two datasets used were buoy_sensor(1) and ocean.

http://citeseer.ist.psu.edu/670978

Real World Examples

http://media.moddb.com/images/games/1/15/14252/ArmA2-OpArr-march2010-008.jpg

Recognizing motion primitives

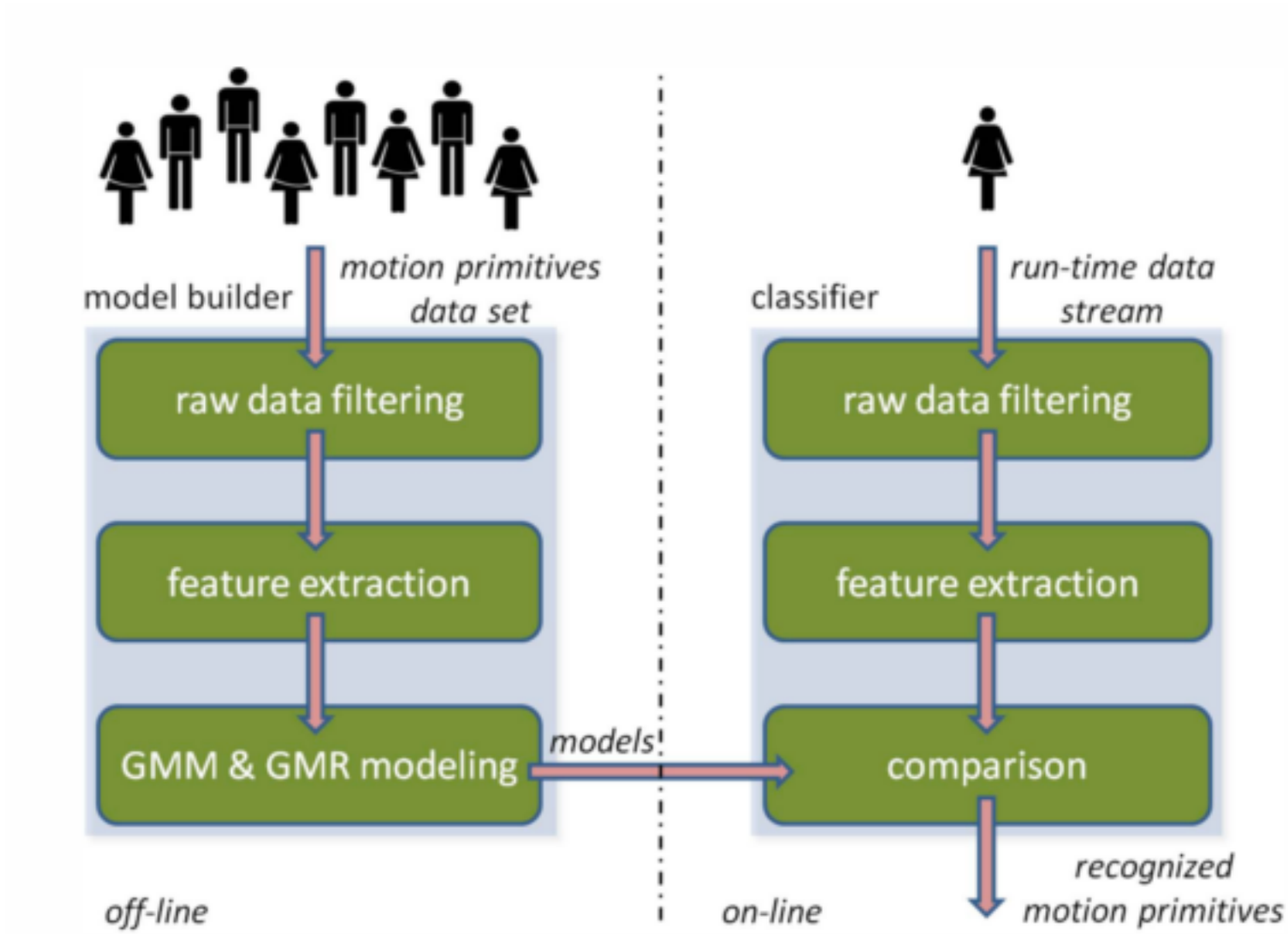


Fig. 1. System architecture.

http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6630784

Recognizing motion primitives

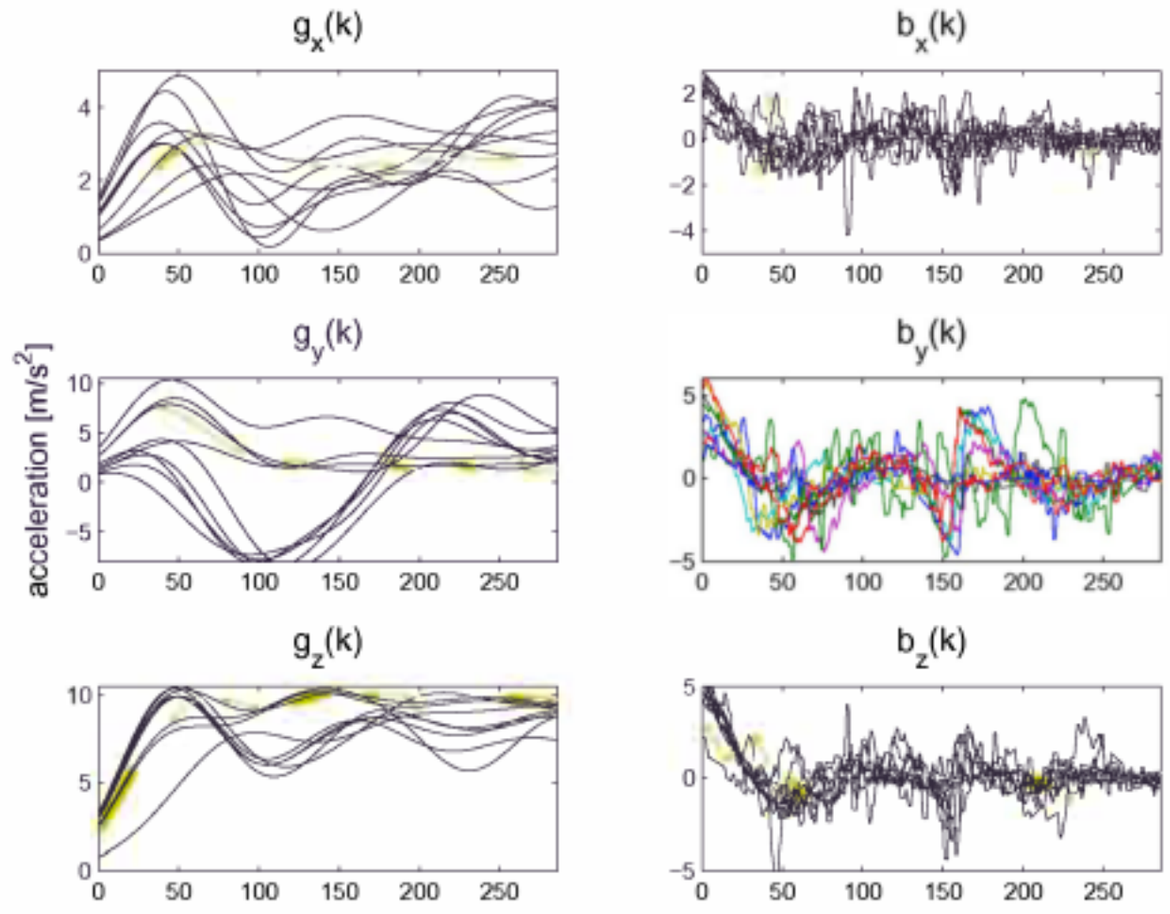


Fig. 2. Feature curves extracted from the trials of the *eating with knife and fork* motion primitive training set.

http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6630784

Recognizing motion primitives

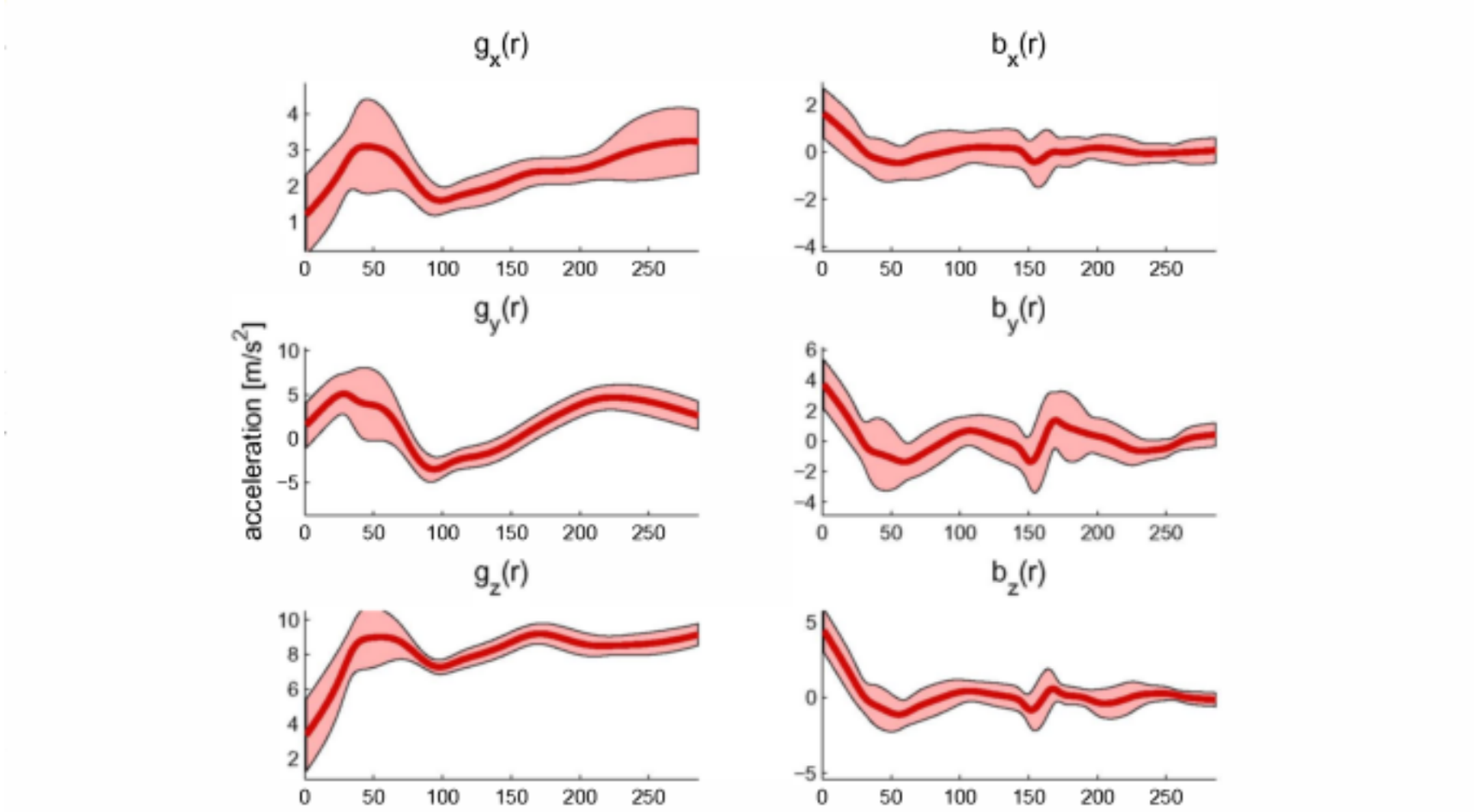


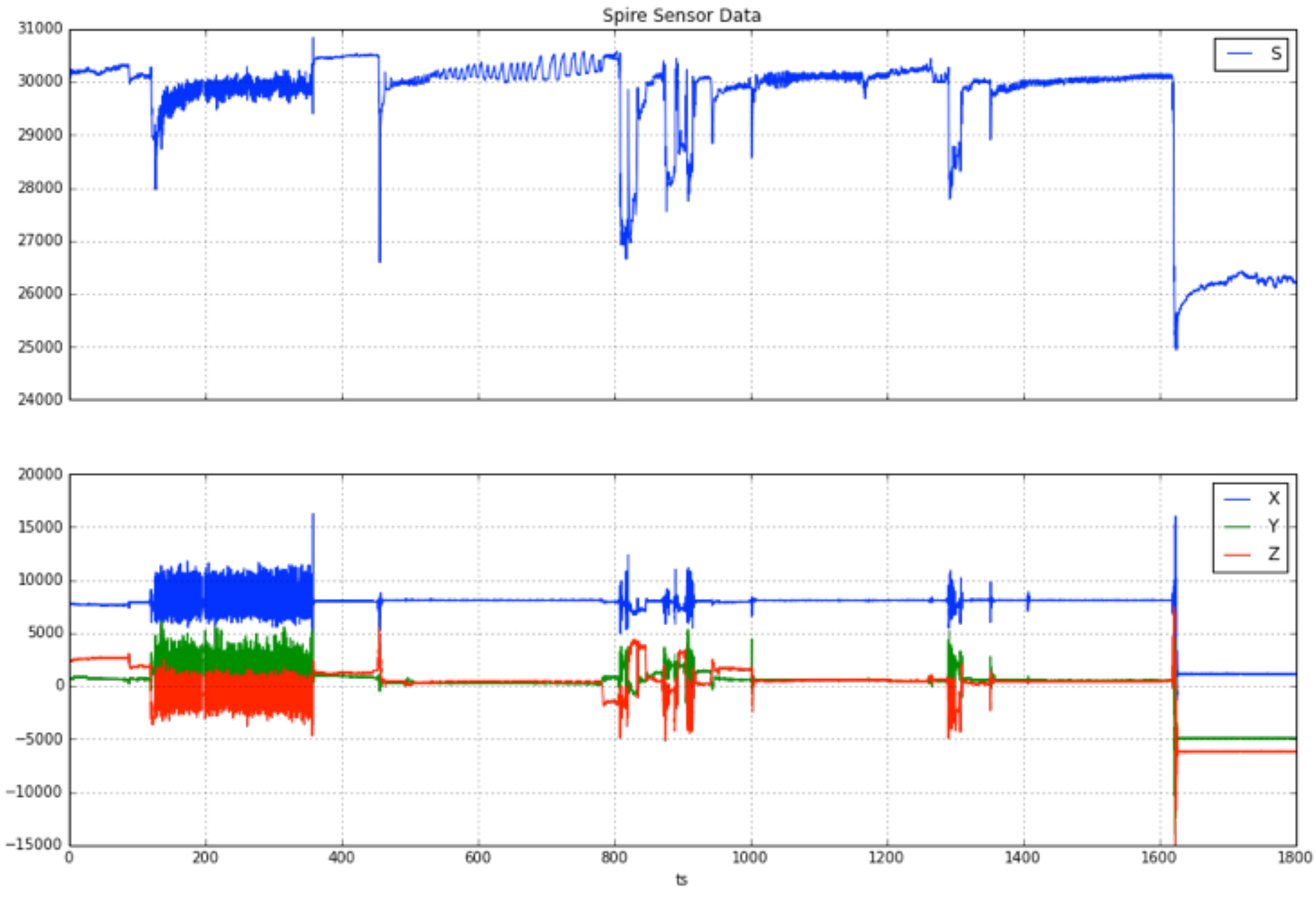
Fig. 3. 2D projections of the *eating with knife and fork* motion primitive model retrieved via GMR.

http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6630784

Recognizing motion primitives

- Trick in this case is to know the beginning of the action

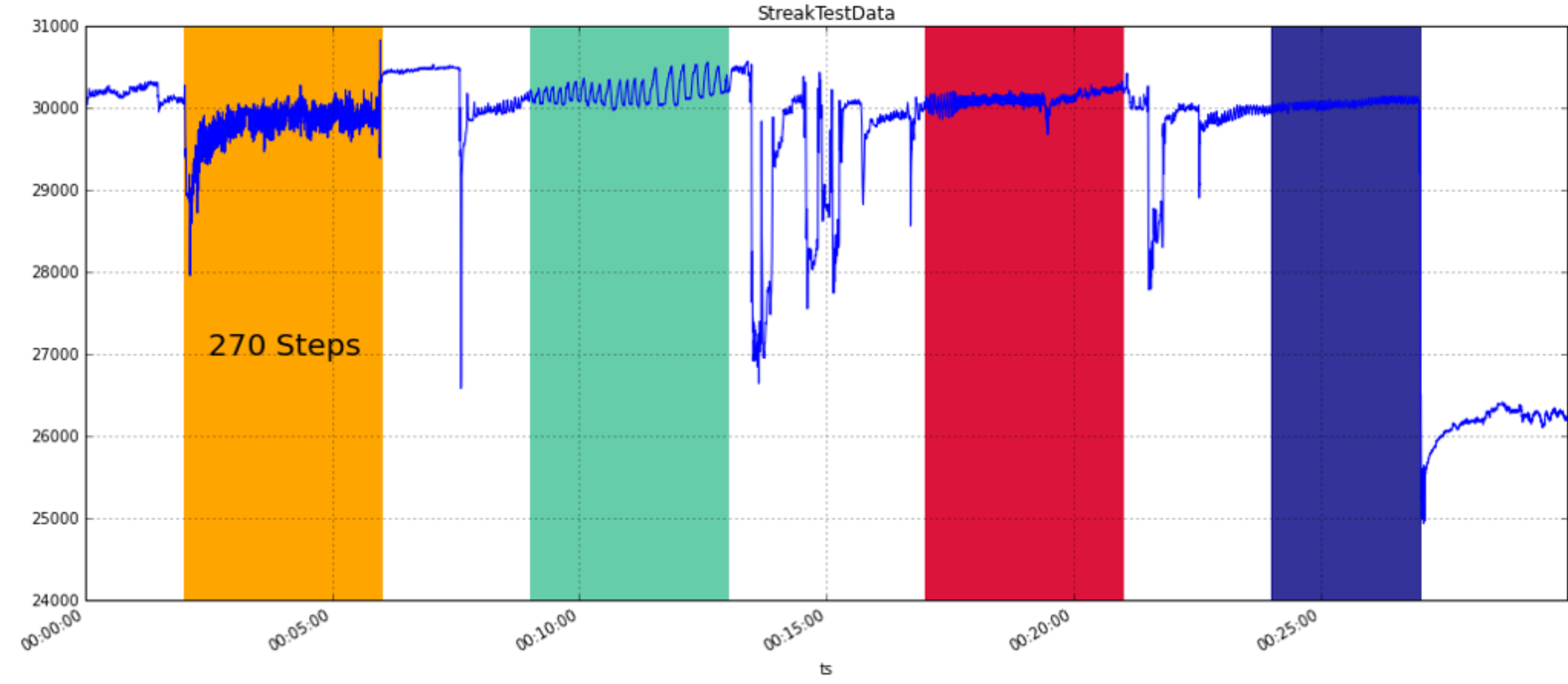
Spire



Spire

- Wearable sensor
- Detects physical activity
- Counts steps
- Measures calories
- Detects Breathing Patterns
- Classifies Breathing in different States of Mind

Spire


StreakTestData
31000
30000
29000
28000
27000
26000
25000
24000
270 Steps
00:00:00
00:05:00
00:10:00
00:15:00
00:20:00
00:25:00
ts

TSS glossary

- Online VS Offline algorithms
- Frequency-domain VS time-domain
- Parametric VS non-parametric

Online

- an online algorithm is one that can process its input piece-by-piece in a serial fashion, i.e., in the order that the input is fed to the algorithm, without having the entire input available from the start.

http://www.pxleyes.com/blog/wp-content/uploads/showcases/sequence-photography/41.jpg

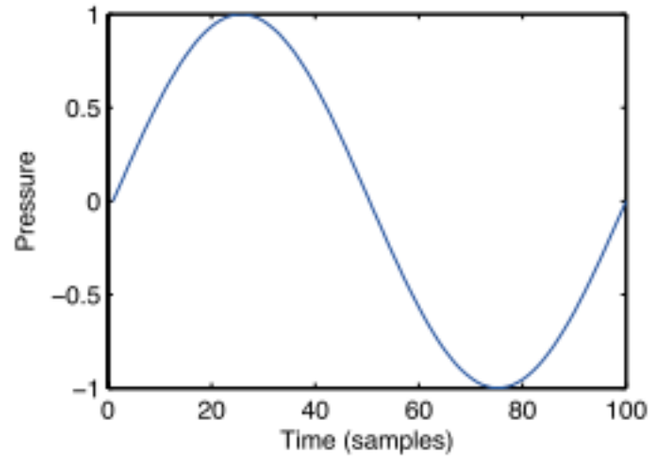
Offline

- an offline algorithm is given the whole problem data from the beginning and is required to output an answer which solves the problem at hand.

http://www.pxleyes.com/blog/wp-content/uploads/showcases/sequence-photography/41.jpg

Frequency domain

- Sinusoids
  - simple waveform
  - single frequency



Frequency domain

- Sinusoids
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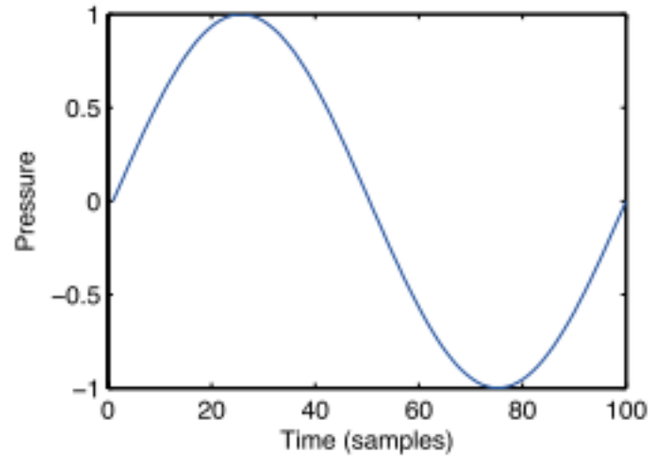
  - single frequency



- 3 parameters:
  - s(t) = a * sin(f * t + p)
    - a = amplitude
    - f = frequency
    - p = phase

Frequency domain

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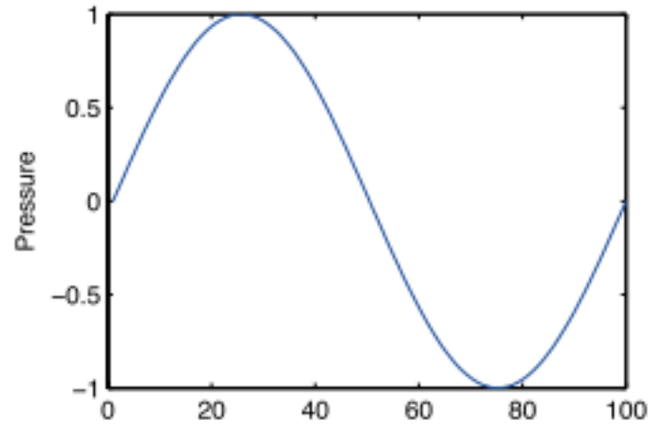
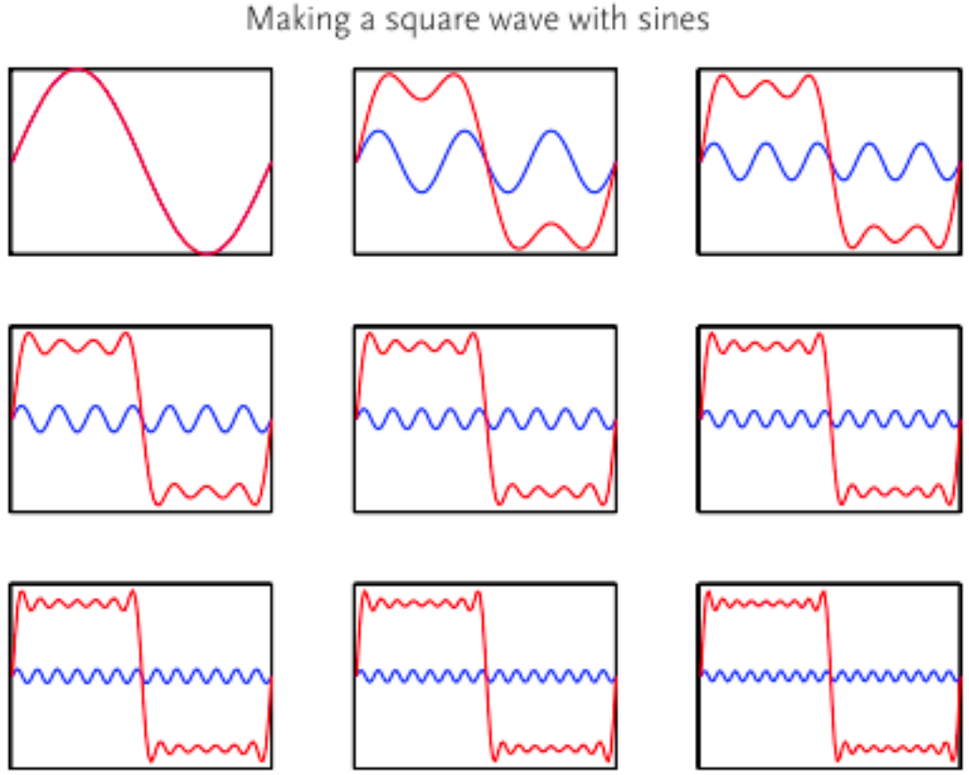
  - 3 parameters:
    - s(t) = a * sin(f * t + p)
      - a = amplitude
      - f = frequency
      - p = phase
  - They are excellent building blocks

$$s_N(x) = \frac{A_0}{2} + \sum_{n=1}^{N} A_n \cdot \sin\left(\frac{2\pi n x}{P} + \phi_n\right), \quad \text{for integer } N \geq 1.$$





Building blocks

- Sinusoids
  - simple waveform
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    - s(t) = a * sin(f * t + p)
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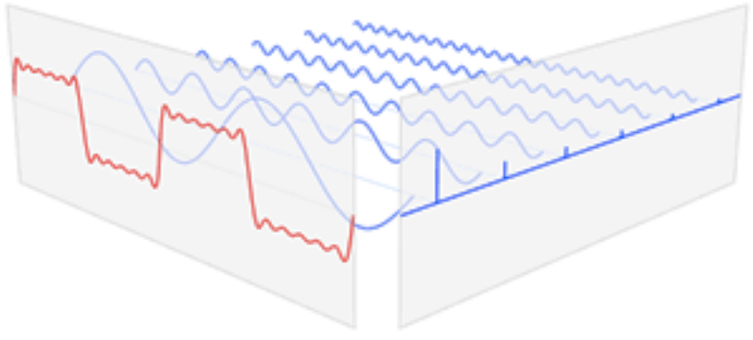
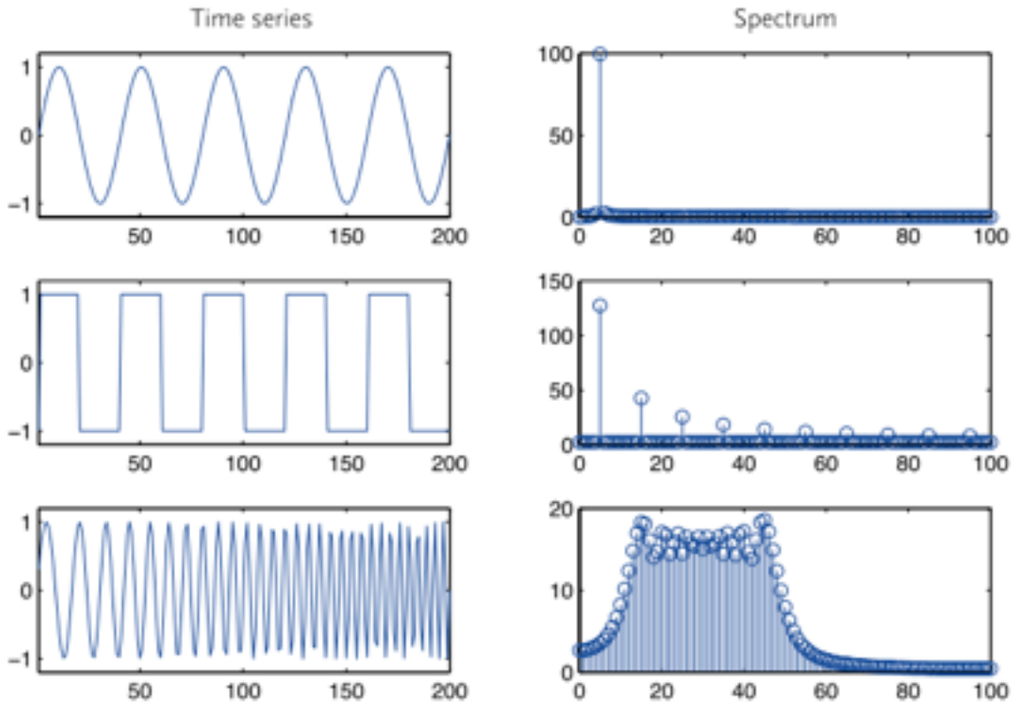
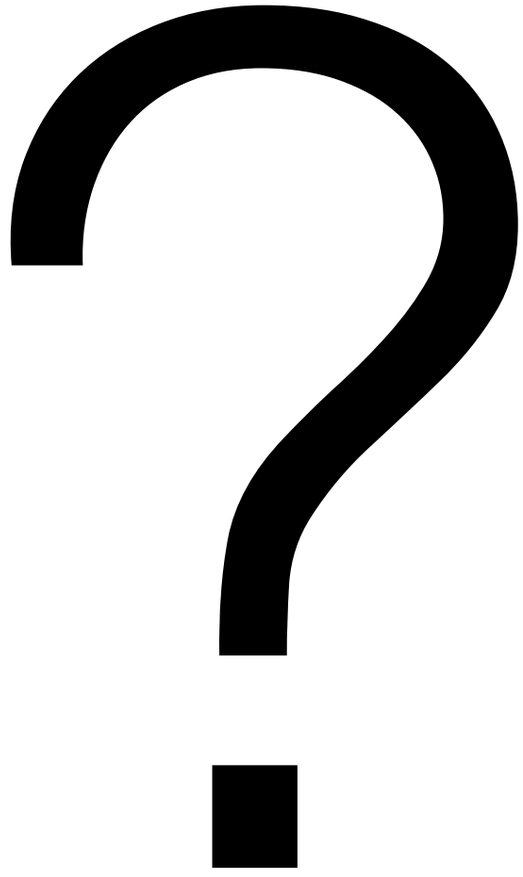


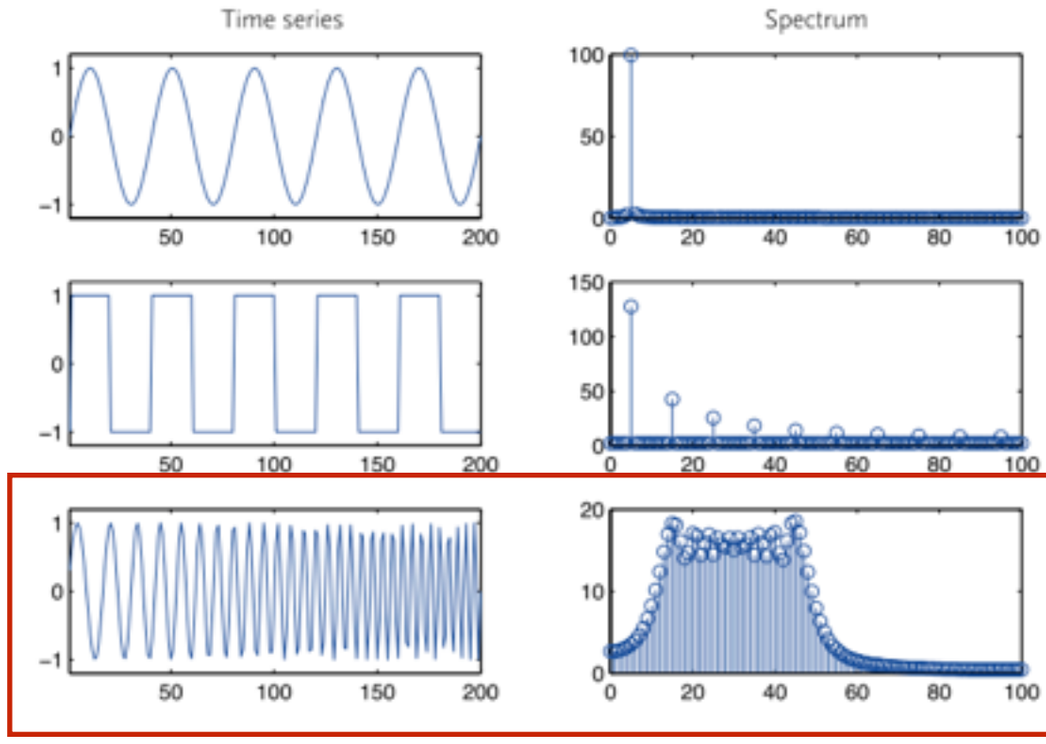
Frequency Spectrum

- Time series can be decomposed in terms of “sinusoid presence”
  - That’s the frequency spectrum
- No temporal information in this representation, only frequency
- So a signal with changing frequency becomes a smeared spike



How can we solve this?



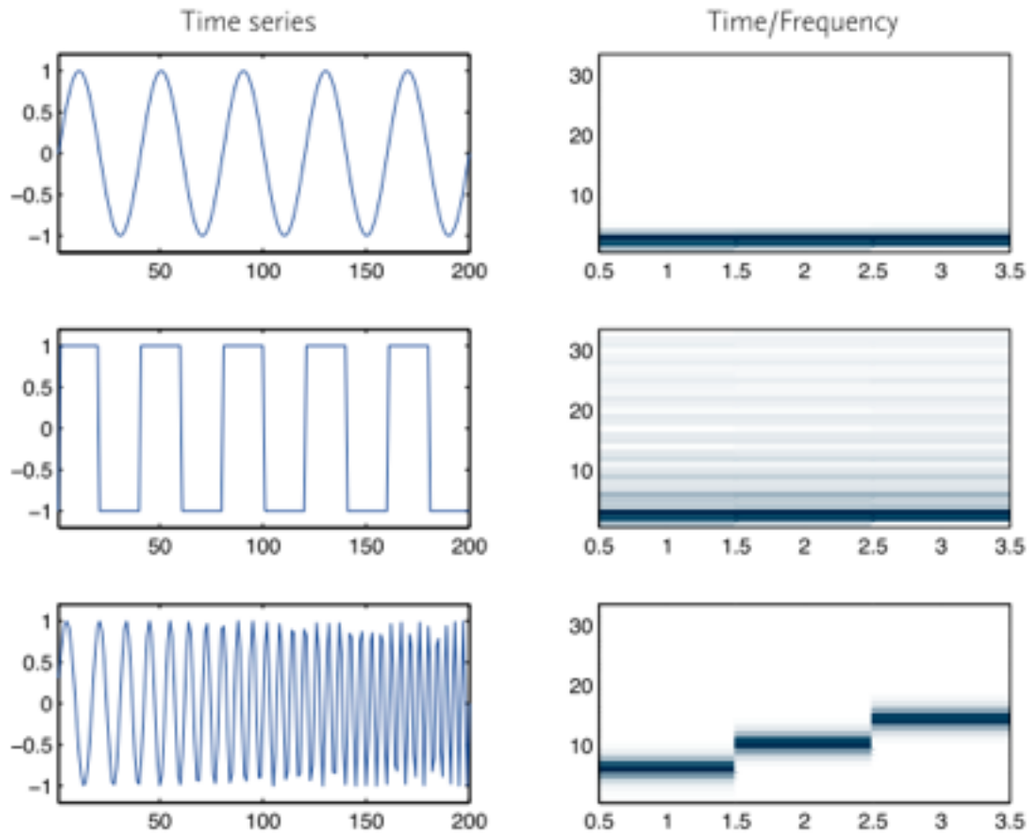


Time/Frequency Representation

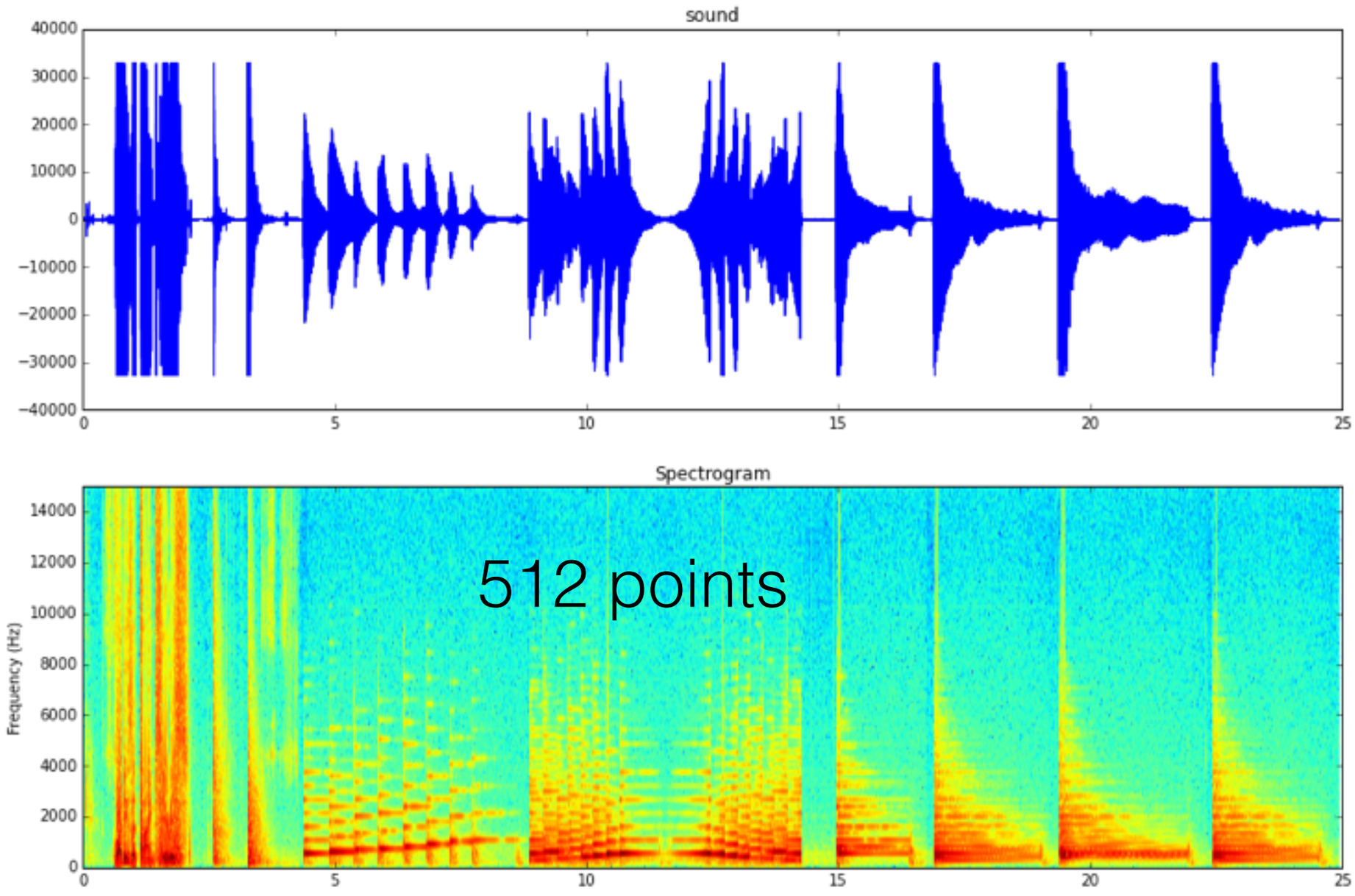
- Time-ordered series of frequency compositions

- Calculate Frequency Spectrum in each window

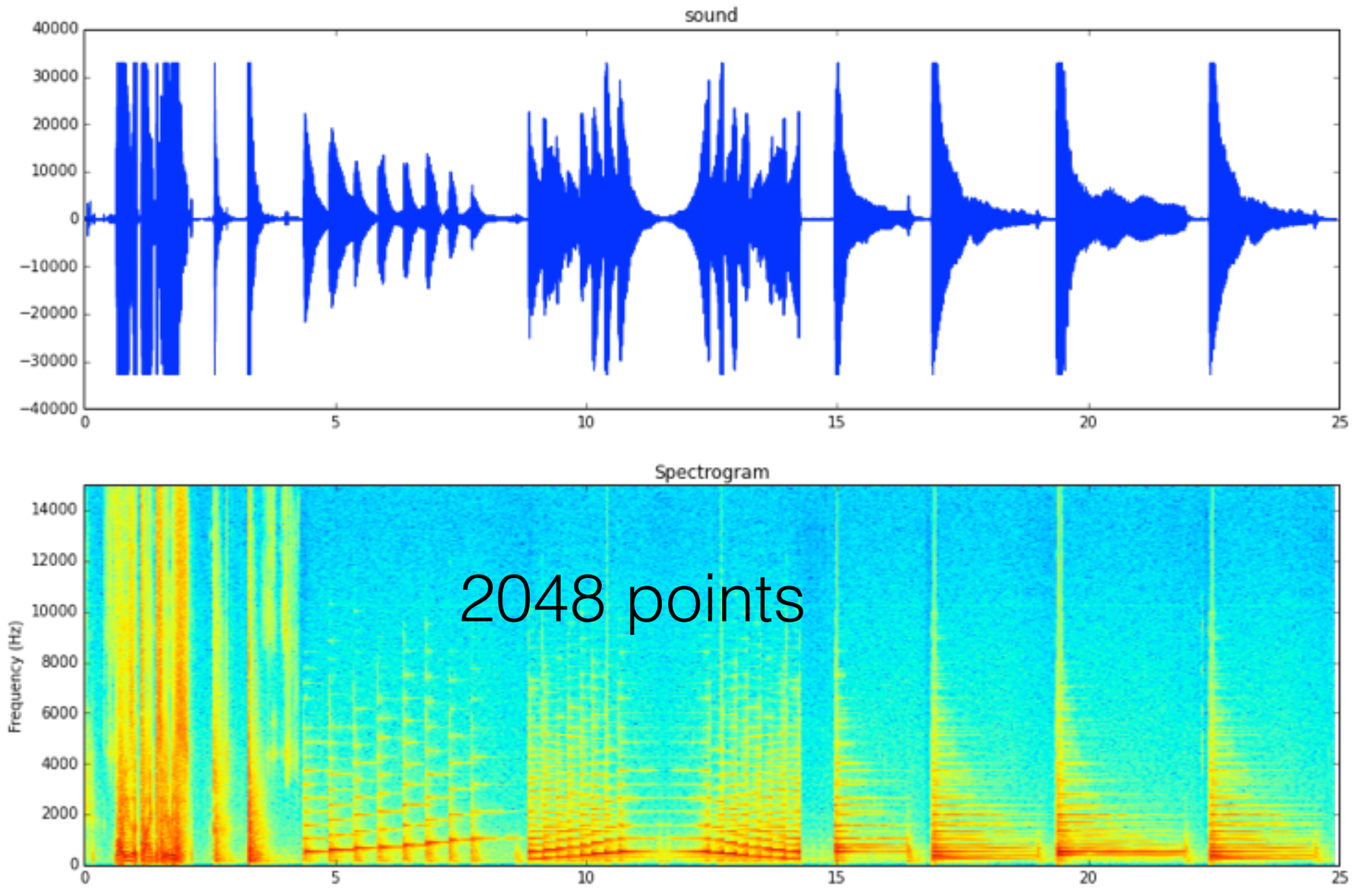
- Works really well when information is encoded in the frequency, like for example … in sounds!



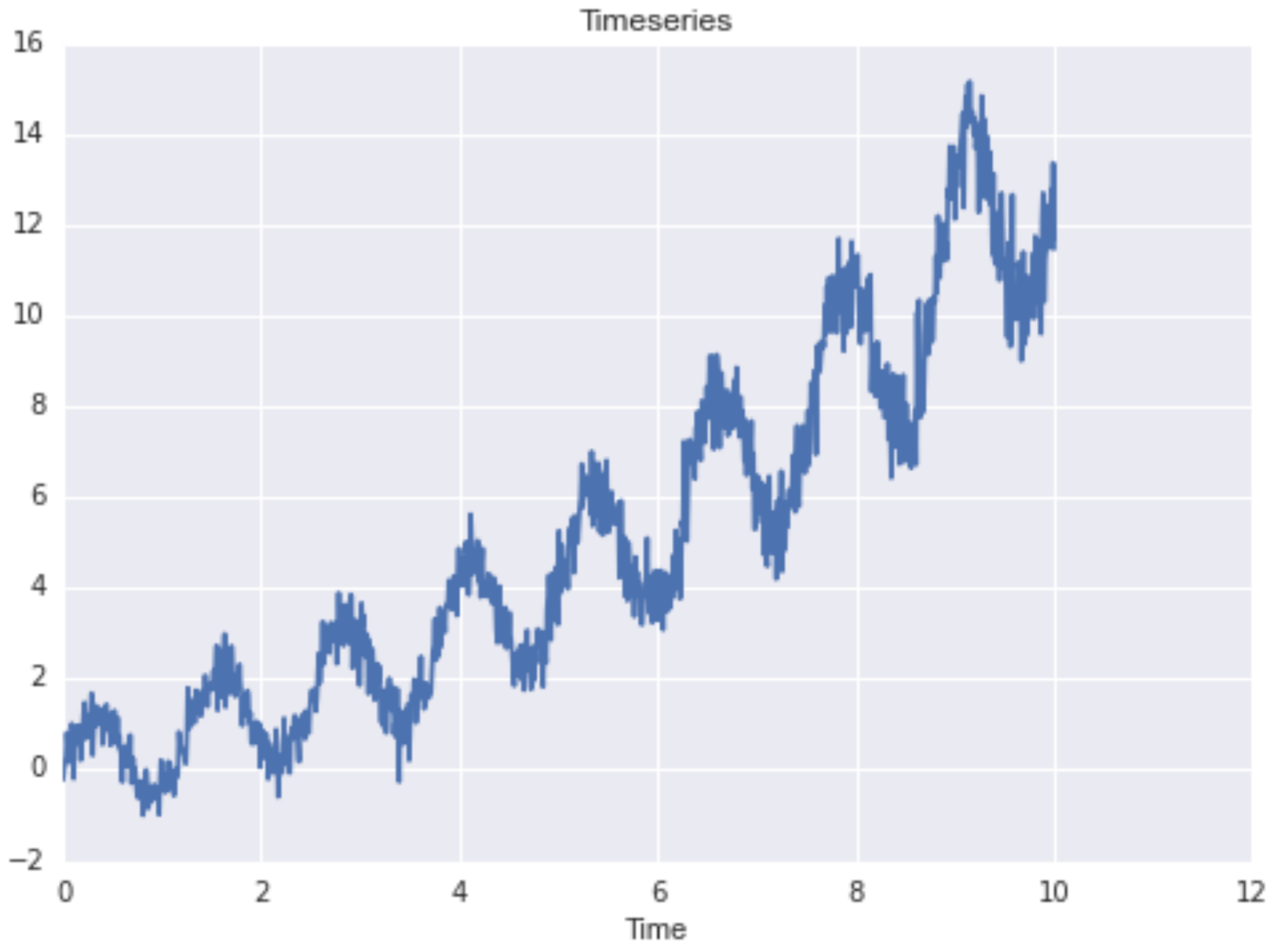
Spectrogram



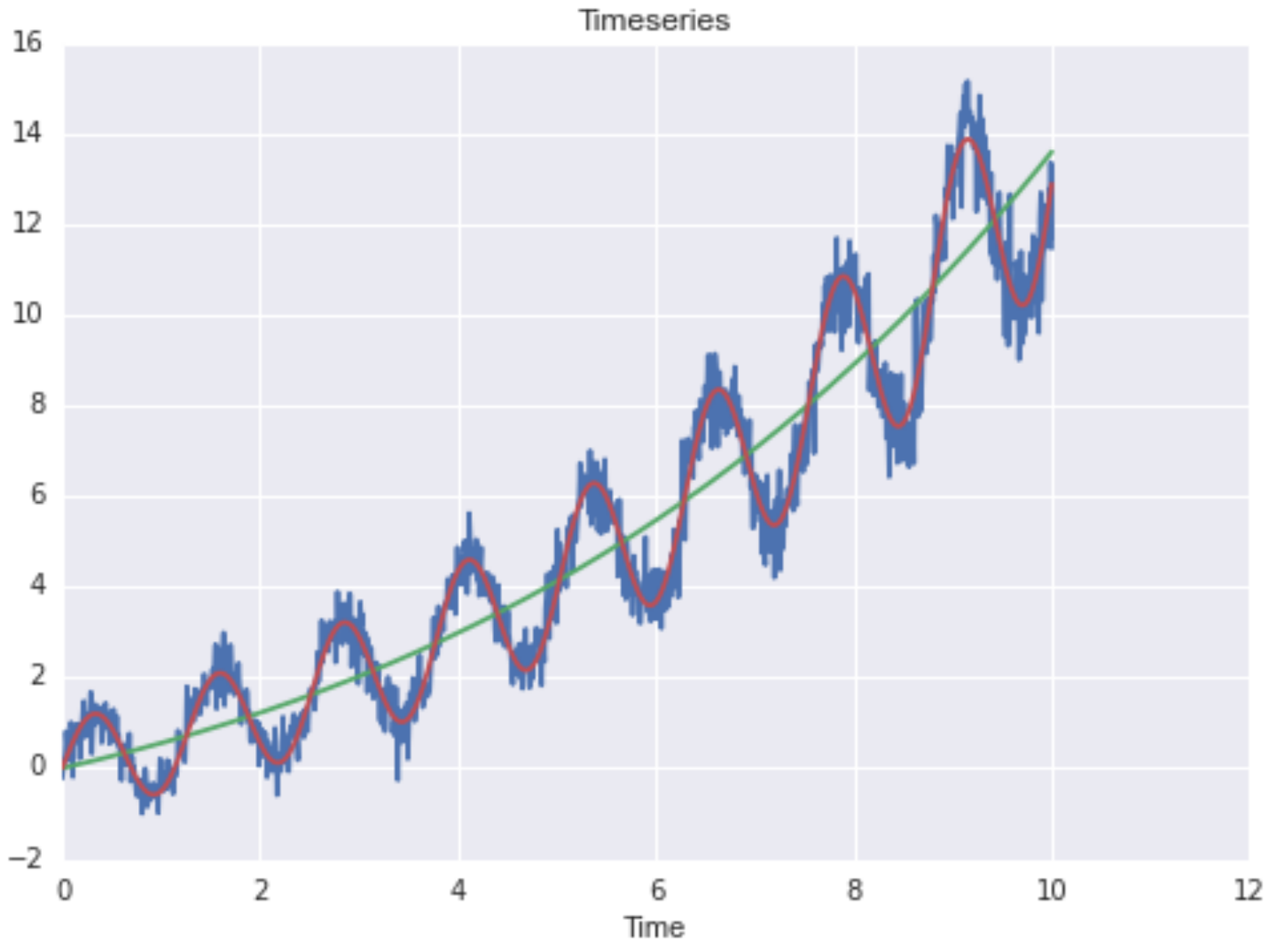
Spectrogram



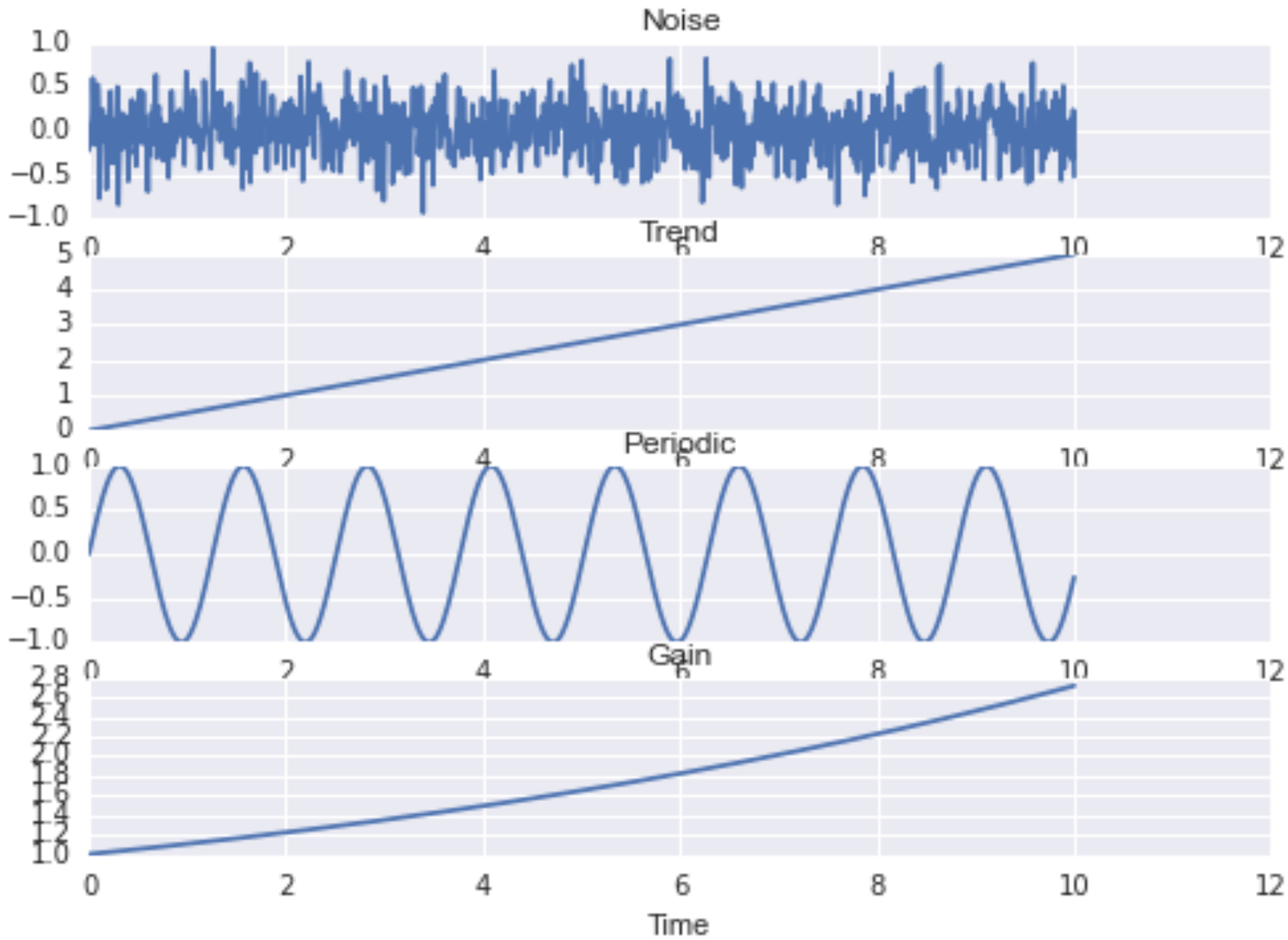
Parametric or Not?



Parametric or Not?



Parametric or Not?

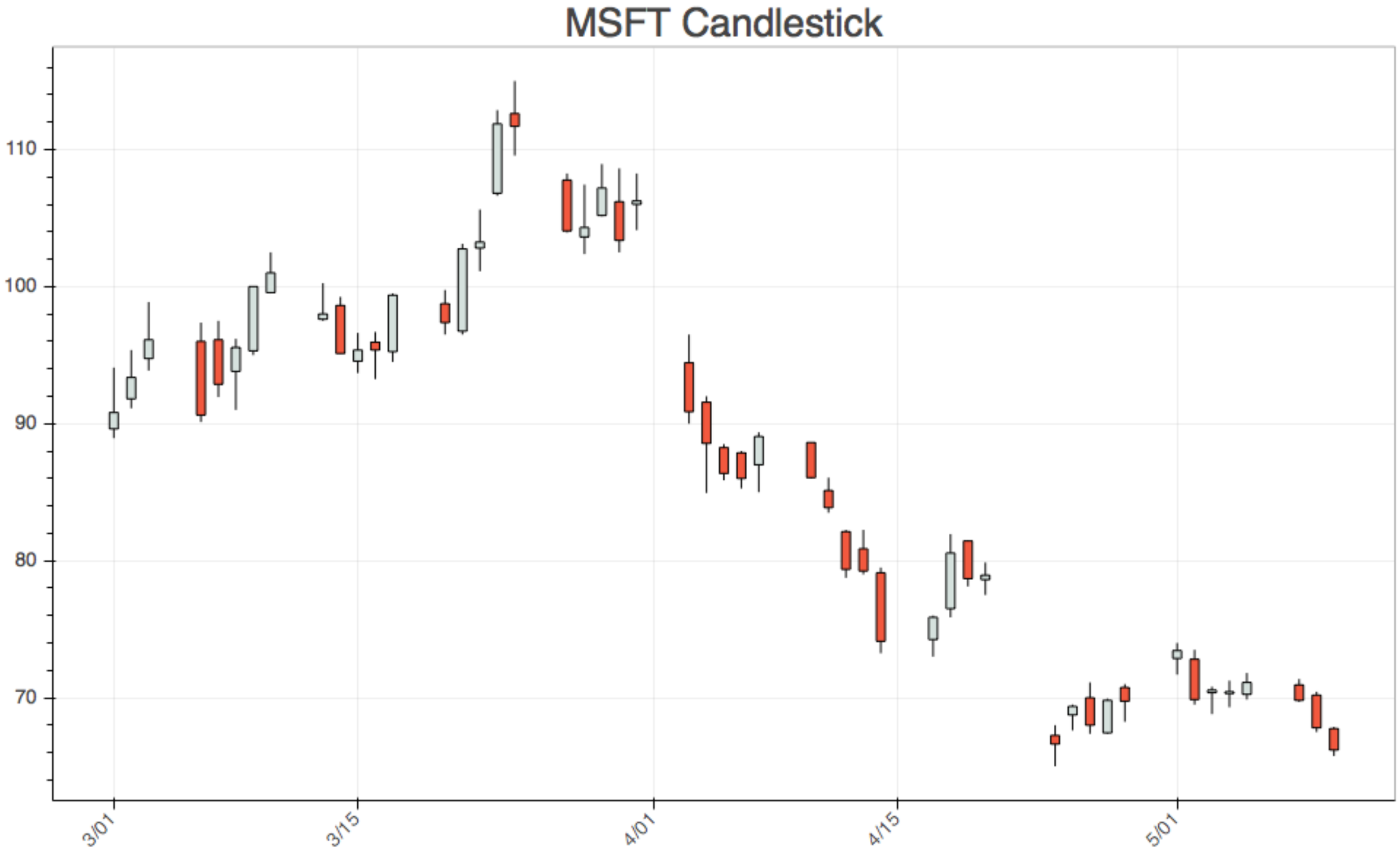


Other Tools & Tricks

http://rack.1.mshcdn.com/media/ZgkyMDEzLzA1LzA5LzJhL21hZ2ljdHJpY2suMjk4MWIuanBnCnAJdGh1bWIJOTUweDUzNCMKZQlqcGc/f87f0b90/aef/magic-trick.jpg

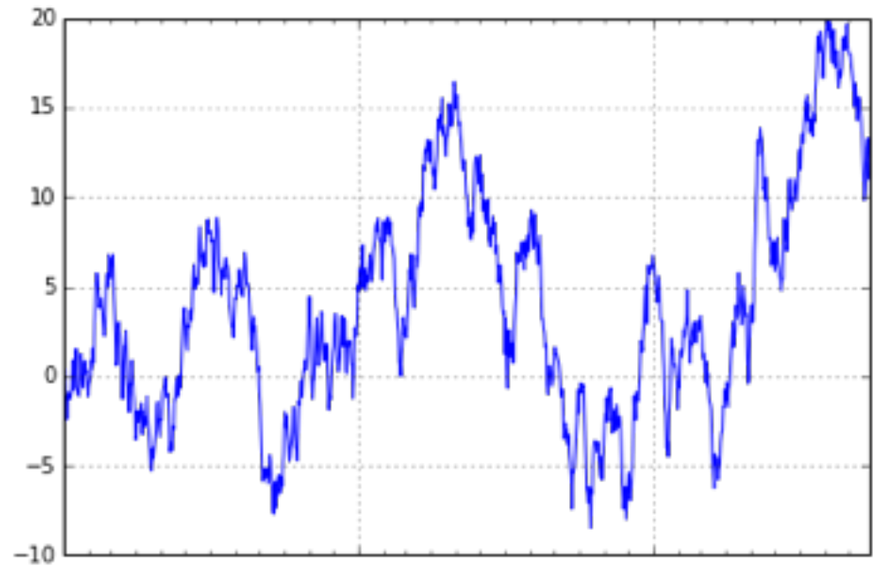
Other Tools & Tricks

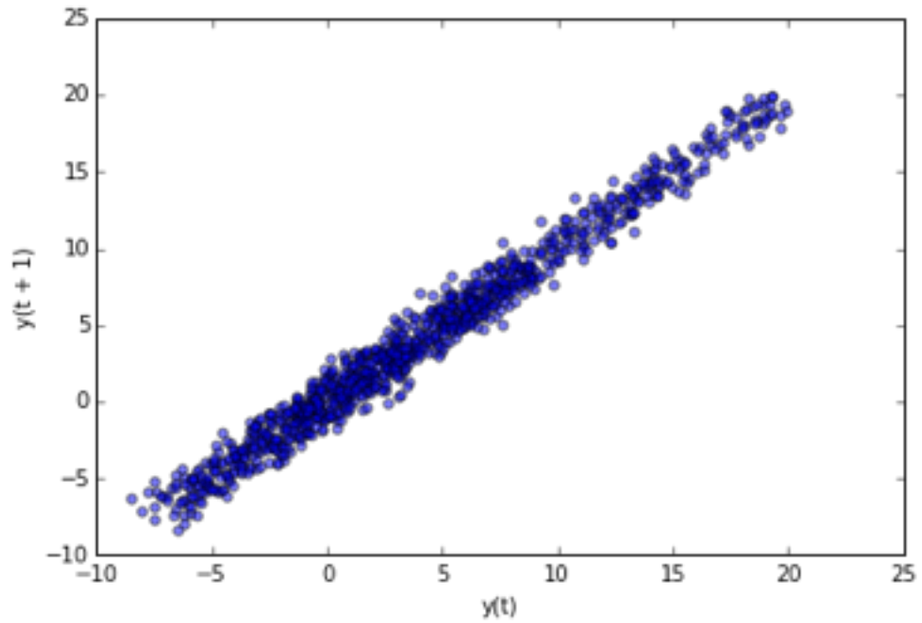
- Candlestick plot
- Lag plot
- Autocorrelation plot

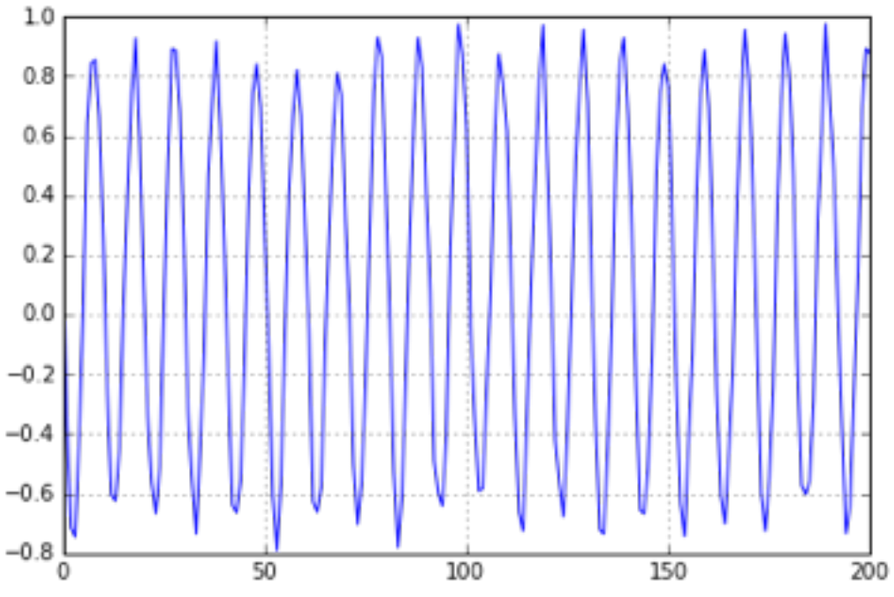


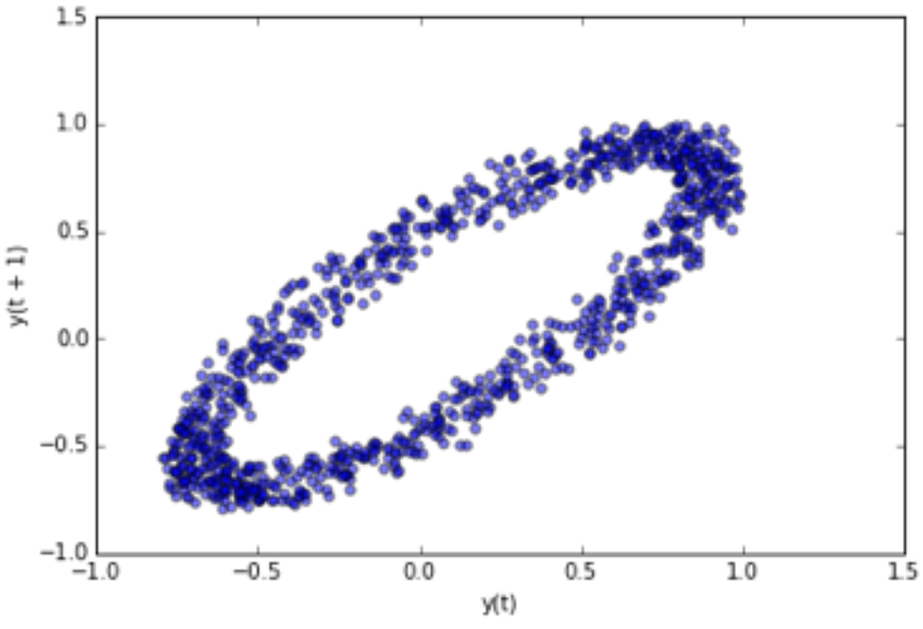
http://bokeh.pydata.org/en/latest/docs/gallery/candlestick.html

Lag Plot



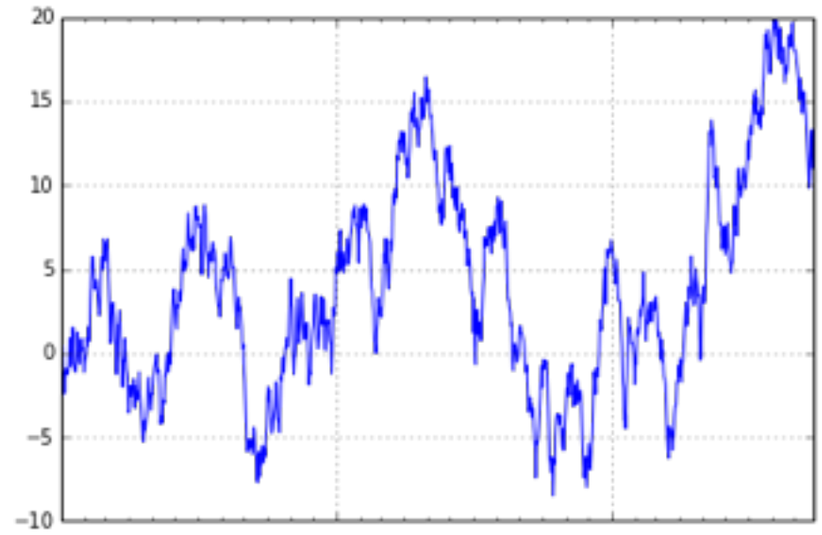


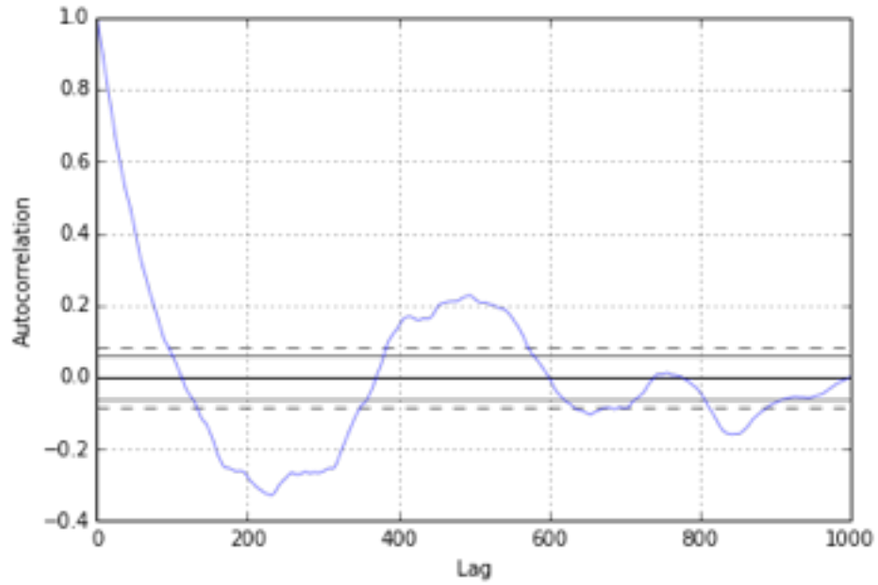


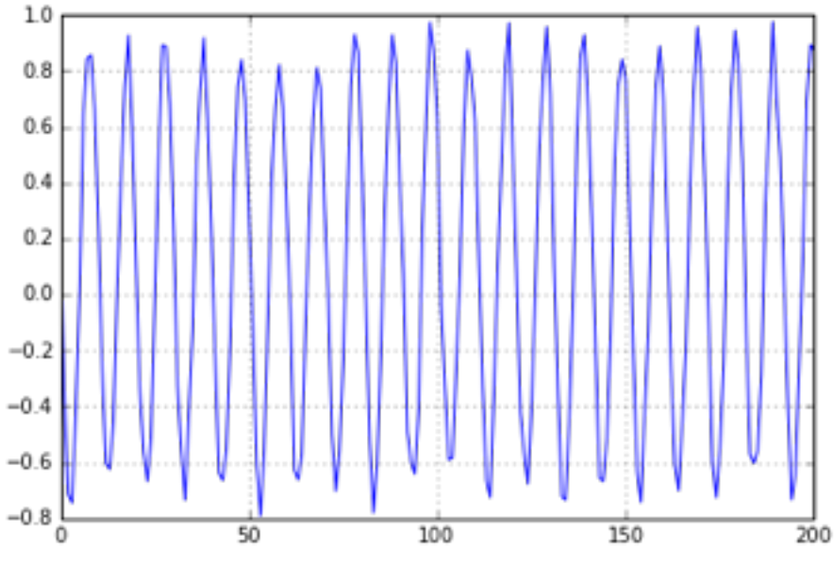


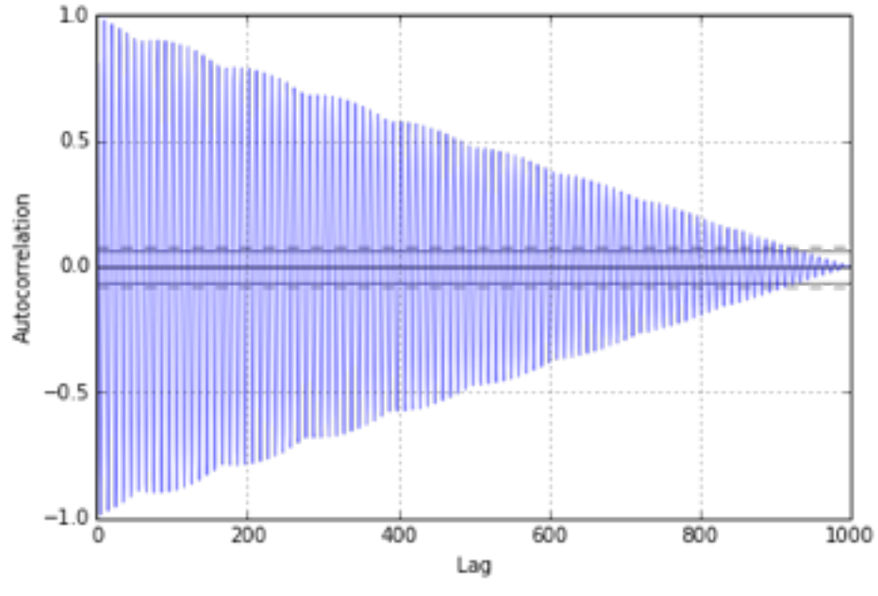
http://pandas.pydata.org/pandas-docs/version/0.15.0/visualization.html#lag-plot

Autocorrelation Function









http://pandas.pydata.org/pandas-docs/version/0.15.0/visualization.html#lag-plot

Validation

- Train - Test split
- Survivor bias
- Labelled data

http://thumbs.dreamstime.com/t/past-now-future-notes-arrow-blackboard-45598002.jpg

Table I. Main Characteristics of Human Activity Recognition Systems

Type	Characteristic	Description
Execution	Offline	The system records the sensor data first. The recognition is performed afterwards. Typically used for non-interactive applications such as health monitoring.
	Online	The system acquires sensor data and processes it in real time. Typically used for activity-based computing and interactive applications in human-computer interaction.
Generalisation	User independent	The system is optimised for working with a large number of users.
	User specific	The system is tailored to a specific user. Performance is usually higher than in the user-independent case, but does not generalise as well to other users.
	Temporal	The system should be robust to temporal variations caused by external conditions (sensor displacement, drifting sensor response such as barometers or gyroscopes)
Recognition	Continuous	The system automatically "spots" the occurrence of activities or gestures in the streaming sensor data.
	Isolated (Segmented)	The system assumes that the sensor data stream is segmented at the start and end of a gesture by an oracle. It only classifies the sensor data in each segment into one of the activity classes. The oracle can be an external system (e.g. cross-modality segmentation) or the experimenter when assessing classification performance in the design phase.
Activities	Periodic	Activities or gestures exhibiting periodicity, such as walking, running, rowing, biking, etc. Sliding window segmentation and frequency-domain features are generally used for classification.
	Sporadic	The activity or gesture occurs sporadically, interspersed with other activities or gestures. Segmentation plays a key role to isolate the subset of data containing the gesture.
	Static	The system deals with the detection of static postures or static pointing gestures.
System model	Stateless	The recognition system does not model the state of the world. Activities are recognised by spotting specific sensor signals. This is currently the dominant approach when dealing with the recognition of activity primitives (e.g. reach, grasp).
	Stateful	The system uses a model of the environment, such as the user's context or an environment map with location of objects. This enhances activity recognition performance, at the expense of more design-time knowledge and a more complex recognition system.

Not to mention the engineering challenges…

- Time Series databases
- Latency
- Online VS Offline…
- http://en.wikipedia.org/wiki/Time_series_database

State of the art…

- Recurrent neural networks (RNNs)

Deep Speech

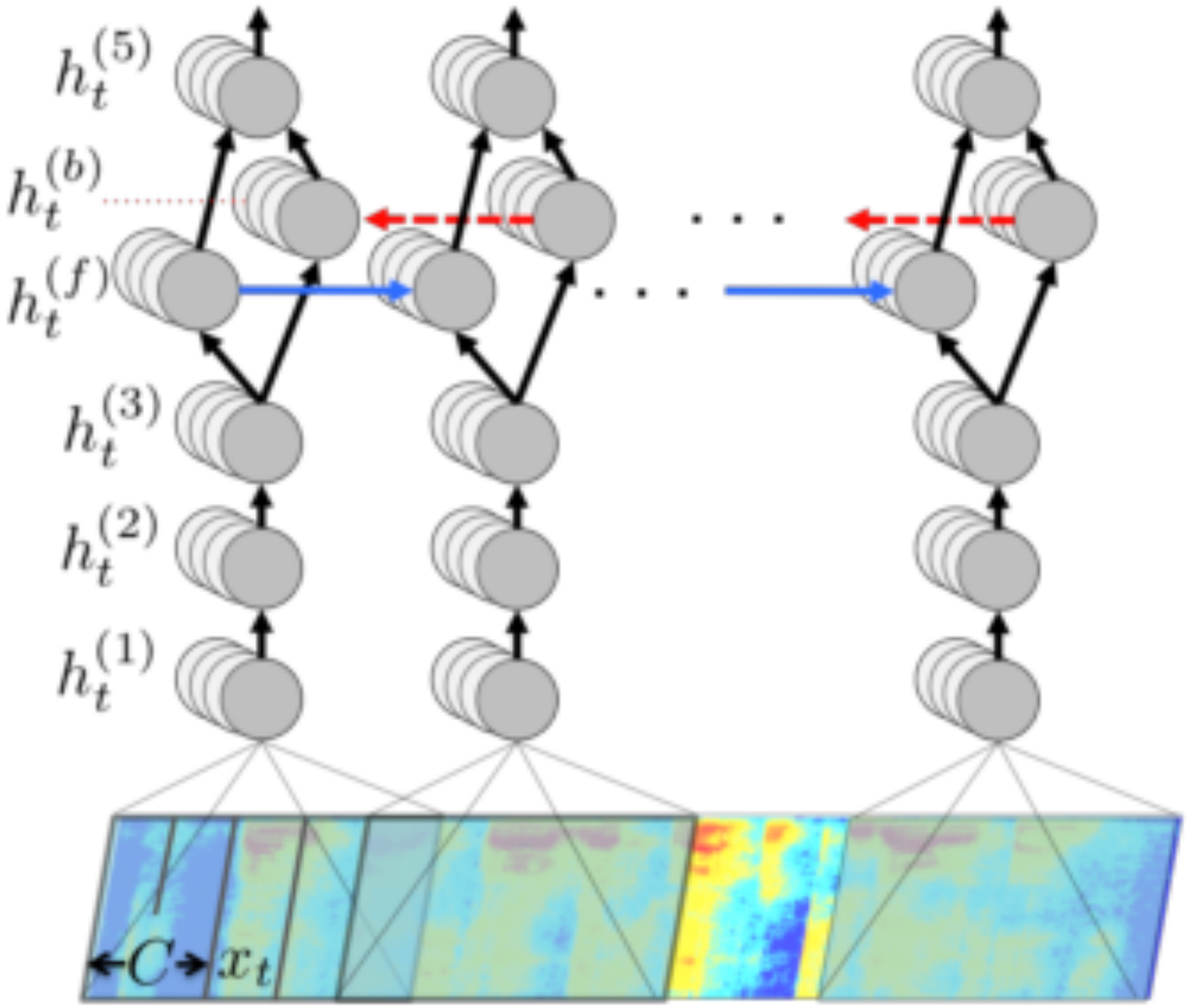


Figure 1: Structure of our RNN model and notation.

arXiv:1412.5567v1

Deep Speech

Model	SWB	CH	Full
Vesely et al. (GMM-HMM BMMI) [43]	18.6	33.0	25.8
Vesely et al. (DNN-HMM sMBR) [43]	12.6	24.1	18.4
Maas et al. (DNN-HMM SWB) [28]	14.6	26.3	20.5
Maas et al. (DNN-HMM FSH) [28]	16.0	23.7	19.9
Seide et al. (CD-DNN) [39]	16.1	n/a	n/a
Kingsbury et al. (DNN-HMM sMBR HF) [22]	13.3	n/a	n/a
Sainath et al. (CNN-HMM) [36]	**11.5**	n/a	n/a
DeepSpeech SWB	20.0	31.8	25.9
DeepSpeech SWB + FSH	13.1	**19.9**	**16.5**

Table 3: Published error rates (%WER) on Switchboard dataset splits. The columns labeled "SWB" and "CH" are respectively the easy and hard subsets of Hub5'00.

Conclusions

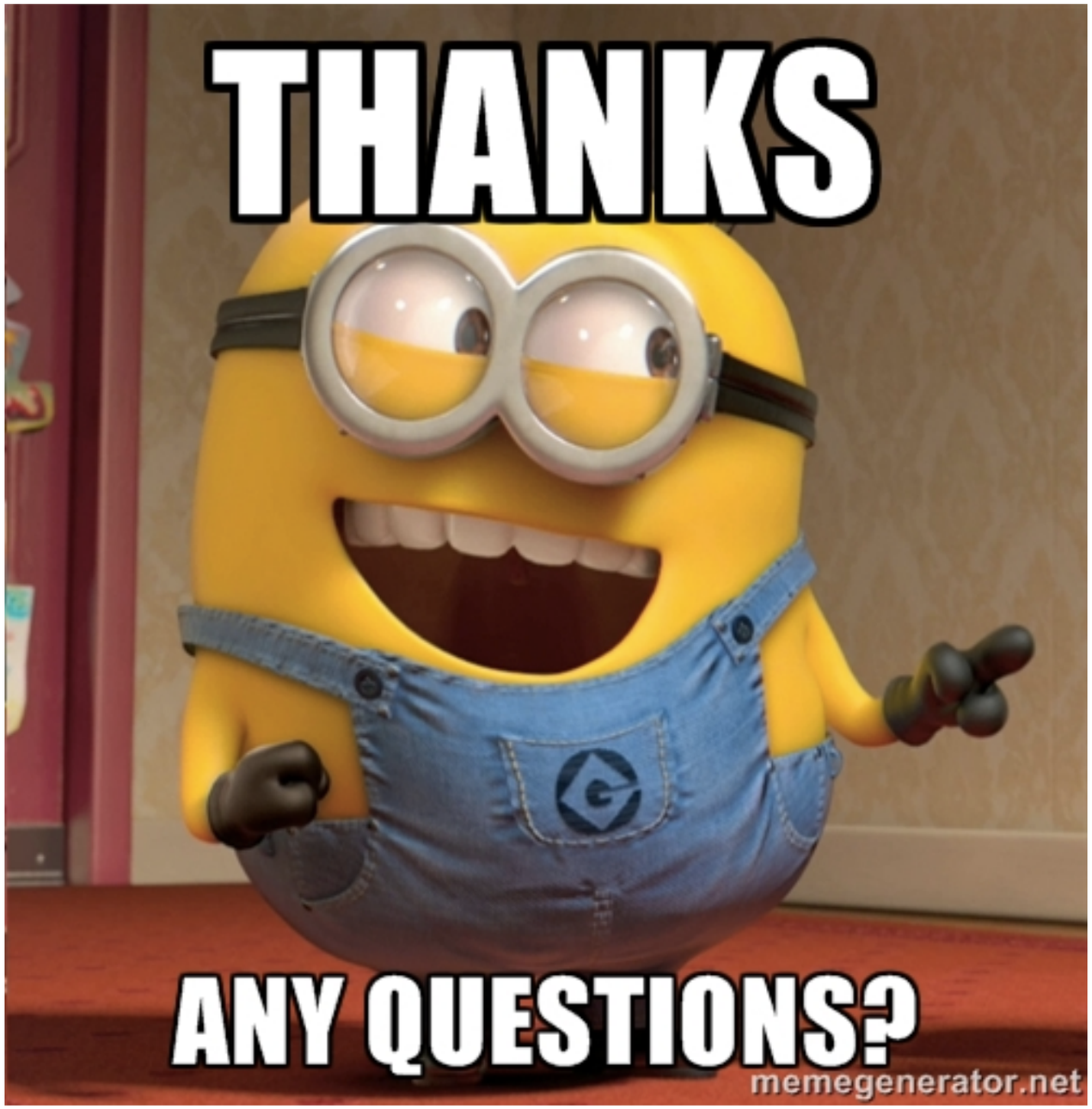
- Time Series Are differente from Flat Datasets
- Preprocessing is very important
- Information can be encoded in time domain or frequency domain or both
- Windows are useful to extract higher order features
- Distance measures between time series useful for clustering
- Choice of tools will depend strongly on the problem to solve

References

- http://en.wikipedia.org/wiki/Time_series

- http://www.cs.ucr.edu/~eamonn/selected_publications.htm

- http://www.stat.berkeley.edu/~bartlett/courses/153-fall2010/lectures/1.pdf



http://i.imgur.com/Ucl2PnS.jpg

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@framosconis