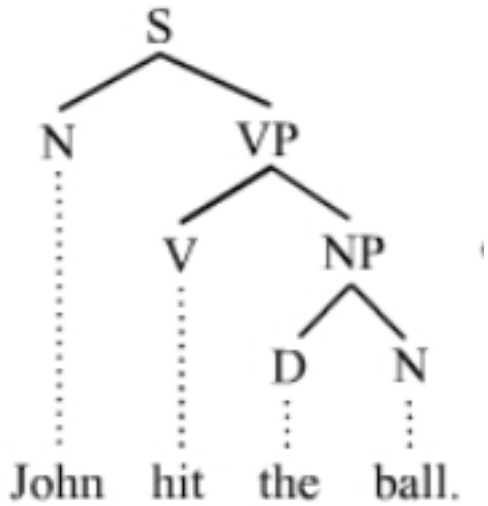
GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

TIME SERIES

DATA SCIENCE IN THE NEWS

LAST TIME:



I. WHAT IS NATURAL LANGUAGE PROCESSING
II. NLP APPLICATIONS
III. BASIC NLP PRACTICE

IV. NLP LABS

QUESTIONS?

WHAT WAS THE MOST INTERESTING THING YOU LEARNT?

WHAT WAS THE HARDEST TO GRASP?

INTRO
MACHINE LEARNING WITH TIME SERIES
TIME SERIES SIMILARITY
TS GLOSSARY
OTHER TOOLS AND TRICKS
REAL WORLD EXAMPLES

- LEARN TERMINOLOGY FOR TIME SERIES
- UNDERSTAND WHY ML ON TS IS DIFFERENT
- KNOW THE DIFFERENCE BETWEEN ONLINE AND OFFLINE ALGORITHMS
- BE ABLE TO APPLY EXPLORATORY VISUALIZATION TO TIME SERIES

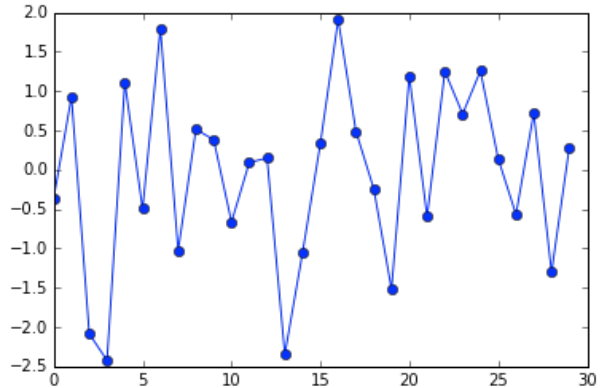
INTRO

WHAT IS A TIME SERIES

- you tell me….

WHAT IS A TIME SERIES

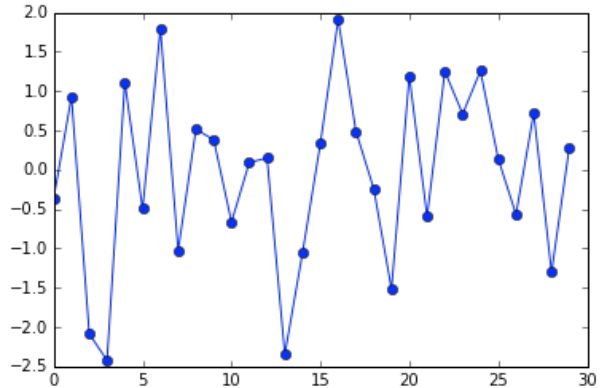
- Sequence of points with timestamps i.e. an ORDERED collection of number



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)

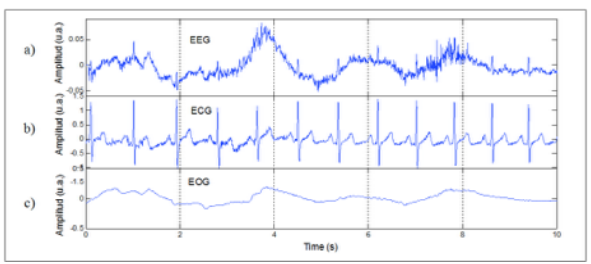


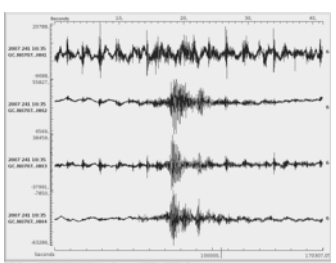
TSS ARE EVERYWHERE

- 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
- …





A TIME SERIES DIFFERENT IS...

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	38.2	-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

TSS ARE DIFFERENT

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

MACHINE LEARNING WITH TIME SERIES LEARN YOU WILL....

MACHINE LEARNING WITH TIME SERIES

MACHINE LEARNING WITH TSS

- example problems….

MACHINE LEARNING WITH TSS

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

PREDICTION

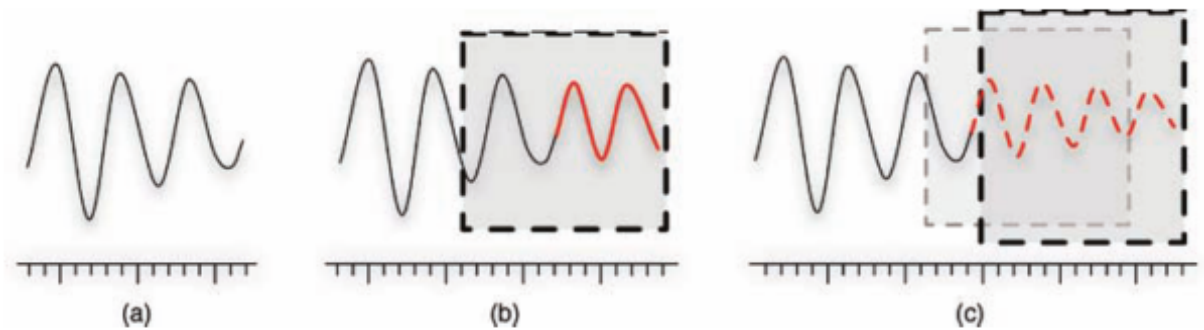


Fig. 5. A typical example of the time-series prediction task. (a) The input time series may exhibit a periodical and thus predictable structure. (b) The goal is to forecast a maximum number of upcoming datapoints within a prediction window. (c) The task becomes really hard when it comes to having *recursive 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

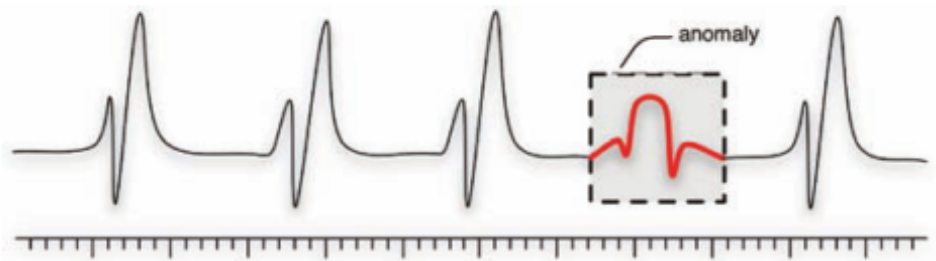


Fig. 6. An idealized example of the anomaly detection task. A long time series which exhibits some kind of periodical structure can be modeled thanks to a reduced pattern of "standard" behavior. The goal is thus to find subsequences that do not follow the model and may therefore be considered as anomalies.

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

SEGMENTATION

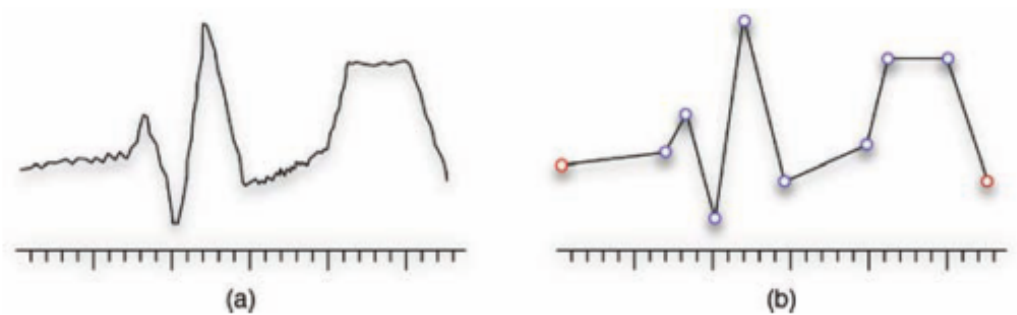


Fig. 4. Example of application of a segmentation system. From (a) usually noisy time series containing a very large number of datapoints, the goal is to find (b) the closest approximation of the input time series with the maximal dimensionality reduction factor without losing any of its essential features.

Find subsections

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

MOTIF DISCOVERY

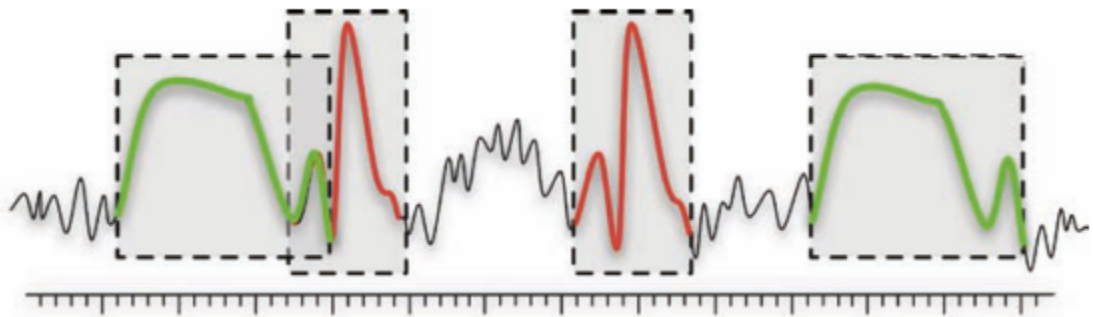


Fig. 7. The task of motif discovery consists in finding every subsequence that appears recurrently in a longer time series. These subsequences are named motifs. This task exhibits a high combinatorial complexity as several motifs can exist within a single series, motifs can be of various lengths, and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

More like a classification problem - find ones similar to each other

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

ML PIPELINE

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

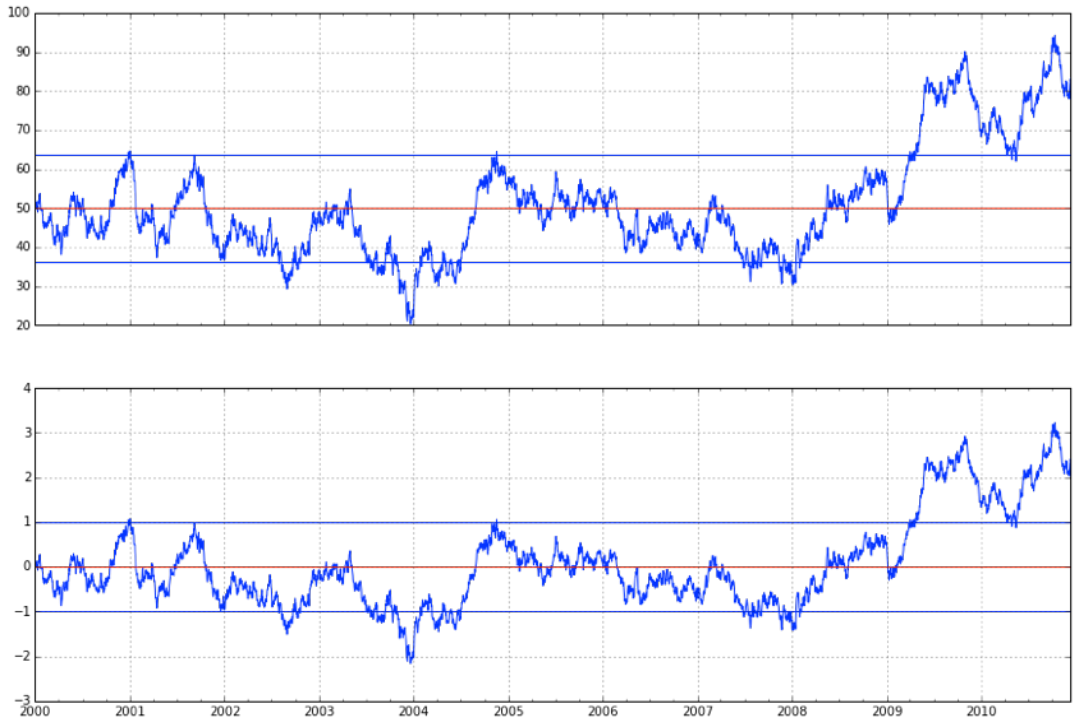
PREPROCESSING

- Normalization
- Filtering

Let’s normalize ‘em TSS

PREPROCESSING

- Normalization

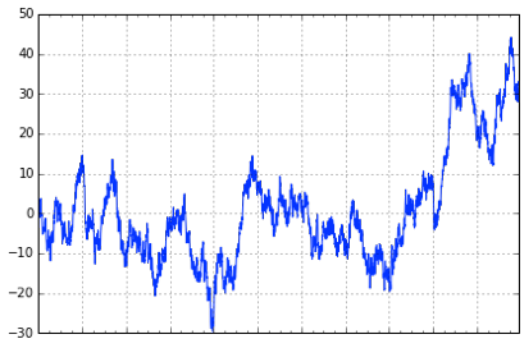


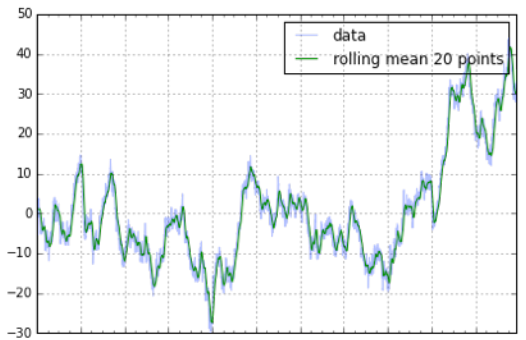
either do standard scaler (subtr mean, divide by std dev) - other times rescale by mean of all time series in set, but not each time

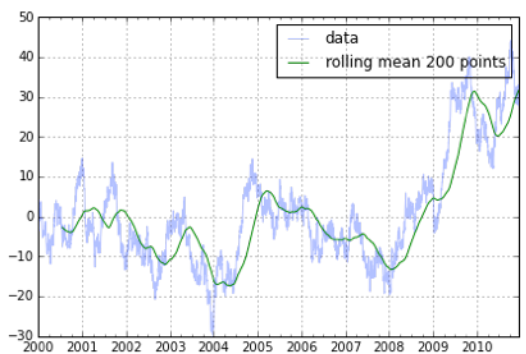
PREPROCESSING

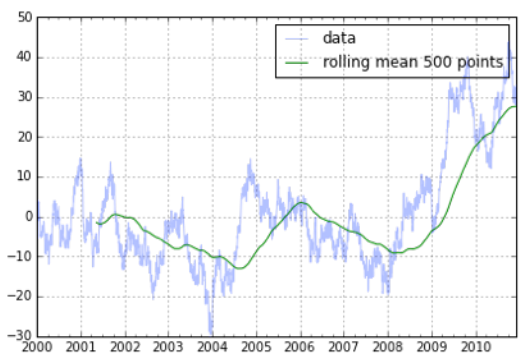
- noise reduction

Take into account the lower trends, remove some of the noise
Moving average: have time series and take
certain # points, take avg, move by 1.
Averaging with a window that moves & fixes









FEATURE EXTRACTION

- Raw data
- Differences
- Rolling windows

FEATURE EXTRACTION

- Raw data
- Differences
- Rolling windows

FEATURE EXTRACTION

- Raw data
- Differences
- Rolling windows

FEATURE EXTRACTION

- Raw data

Use raw data as feature - try to predict what comes next, starting from window of past end points. Take 5 pts before, predict next one.

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

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

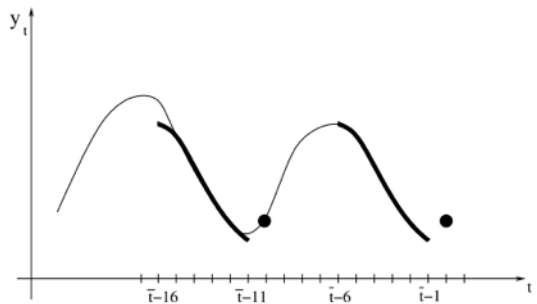


Fig. 2. Nearest-neighbor one-step-ahead forecasts. We want to predict at time $\bar{t}-1$ the next value of the series y of order $n = 6$. The pattern $y_{\bar{t}-16}, y_{\bar{t}-15}, \ldots, y_{\bar{t}-11}$ is the most similar to the pattern $\{y_{\bar{t}-6}, y_{\bar{t}-5}, \ldots, y_{\bar{t}-1}\}$.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

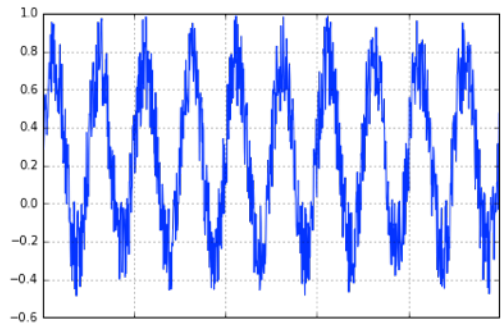
http://link.springer.com/chapter/10.1007/978-3-642-36318-4_3

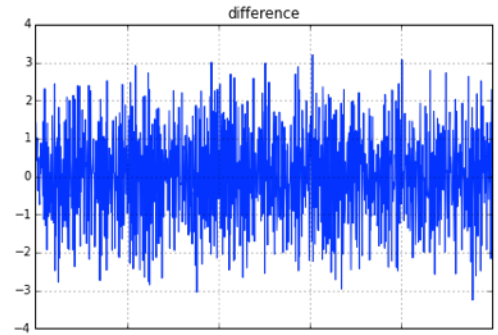
FEATURE EXTRACTION

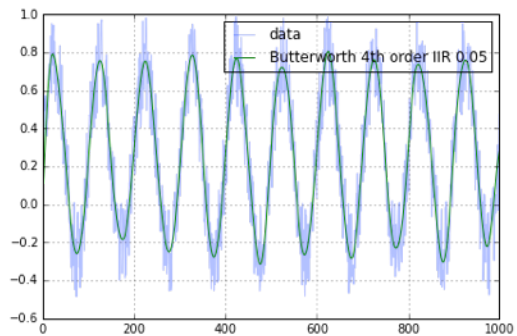
- Raw data
- Differences

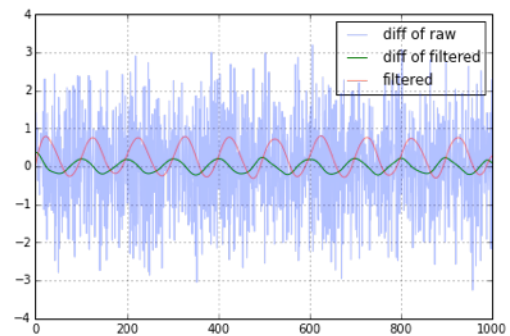
Take derivative of TS, wrt to time - look @ diff btw 2, use that as features to predict what's next. If phenom changing, diffs will catch that change over time.

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





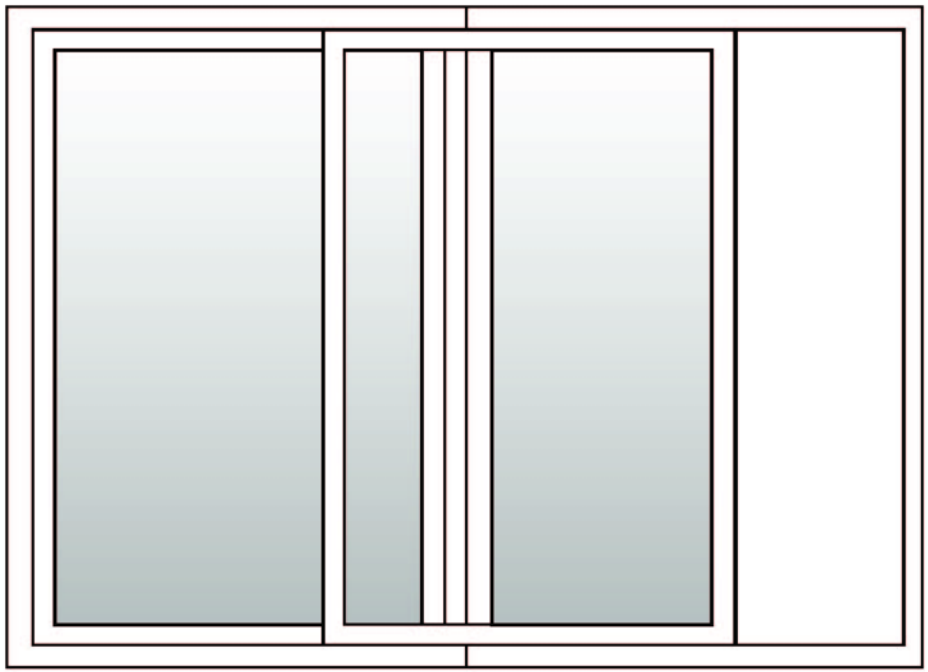




FEATURE EXTRACTION

- Raw data
- Differences
- Rolling windows

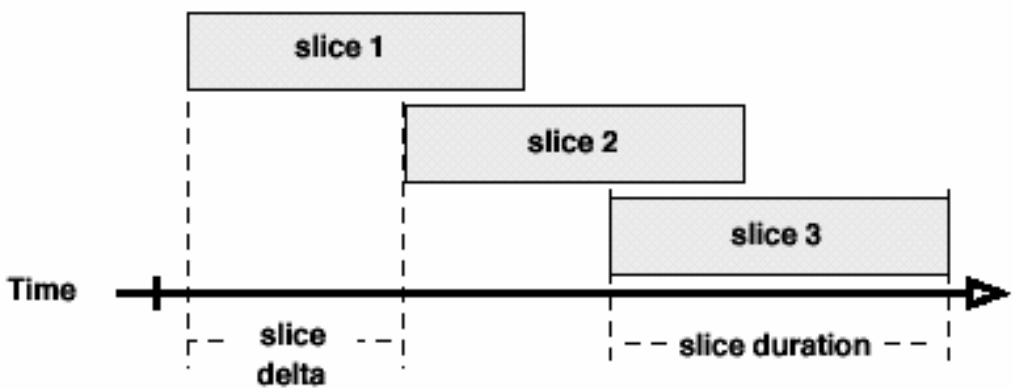
Take a window of certain amt data, extract whatever feat, slide, take another window, extract more feat.



FEATURE EXTRACTION

can do overlapping or disjointed windows. If overlapping, hv higher resolutn of feat. Each window contains indep data, so may not hv correl btw 1 window & next.
TSD --> windows --> matrix that we use for modeling / prediction. The matrix's rows are the slices
Calculate features for the windows (e.g., mean, median, variance)

- 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

FEATURE EXTRACTION

- more complex windows

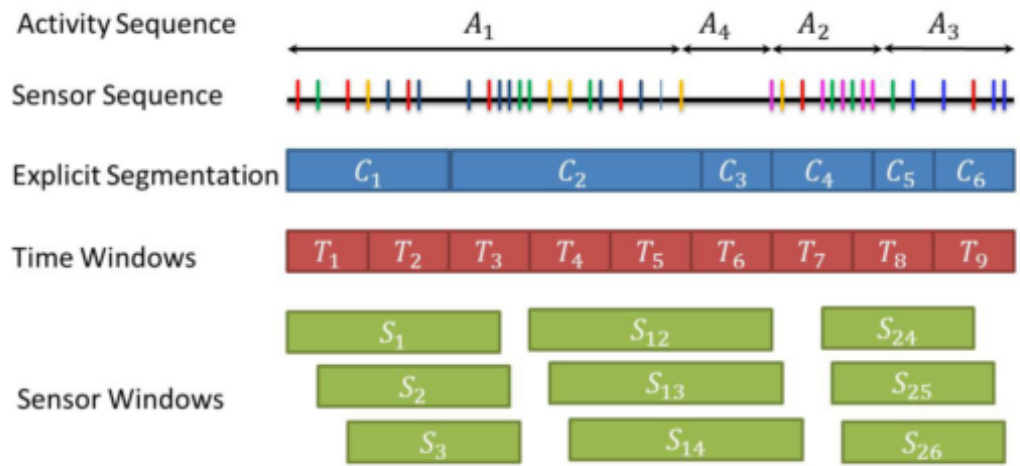


Figure 1: Illustration of the different approaches for stream processing. The different motion/door sensor firings are depicted by the colored vertical lines. The sensor windows are obtained using a sliding window of length 10 sensor events.

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

COMPLETE PIPELINE

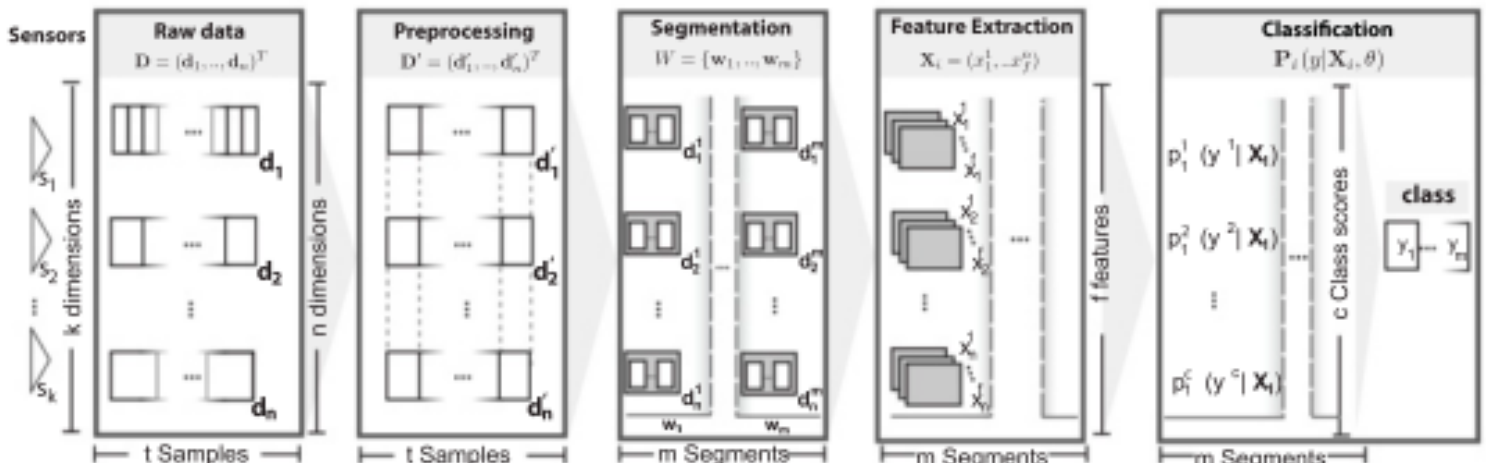


Fig. 1. Typical Activity Recognition Chain (ARC) to recognize activities from wearable sensors. An ARC comprises stages for data acquisition, signal preprocessing and segmentation, feature extraction and selection, training, and classification. Raw signals ($\mathbf{D}$) are first processed ($\mathbf{D}'$) 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

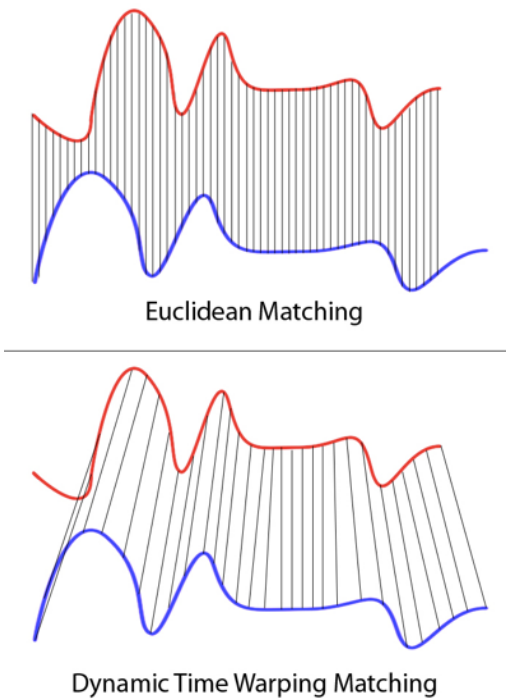
TIME SERIES SIMILARITY

SIMILARITY BETWEEN TIME SERIES

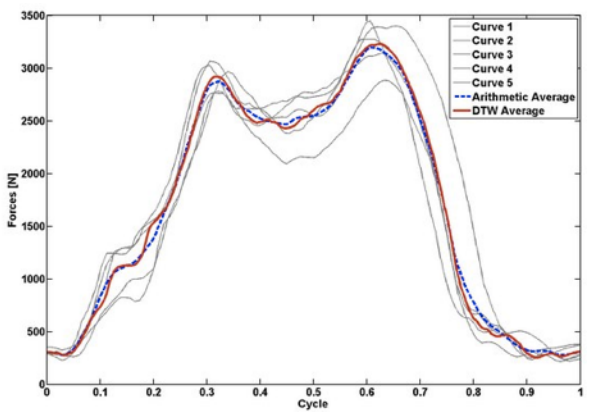
- How did we define distance?

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

SIMILARITY BETWEEN TIME SERIES



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



http://www.orthoload.com/wp-content/uploads/006_6.jpg

DISTANCE MEASURES

Distance between time series
-

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

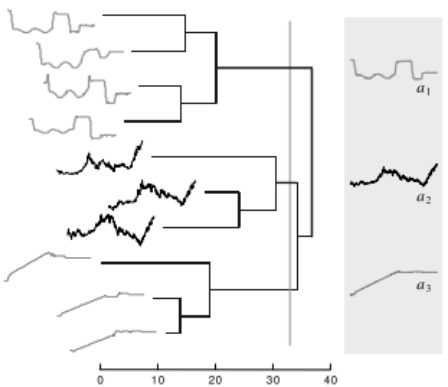


Figure 3. A hierarchical clustering of ten time series. The clustering can be converted to a k partitional clustering by "sliding" a cutting line until it intersects k lines of the dendrograms, then averaging the time series in the k subtrees to form k cluster centers (gray panel).

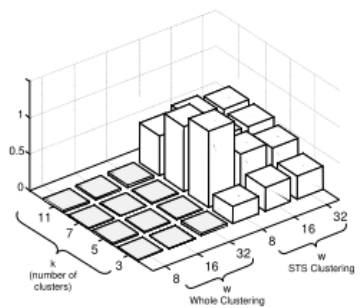


Figure 6. A comparison of the clustering meaningfulness for whole clustering, and STS clustering, using k-means with a variety of parameters. The two datasets used were buoy_sensor(1) and ocean.

Can do a hierarchical clustering and find similarities

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

TS GLOSSARY

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

Takes data in a serial fashion, get one, gives next. Very freq used in stock markets or when trying to build something that does anomaly detection.
Takes data in serial way.
Process time series as it comes.
Offline: I record for 1 day, 1 hr - take whole series and use that as a whole. Knowledge of past and future for that specific window.
Diffs: online - don't know about future, only past. In offline case - know both past and the future.
Taking a snapshot of a certain interval.

OFFLINE

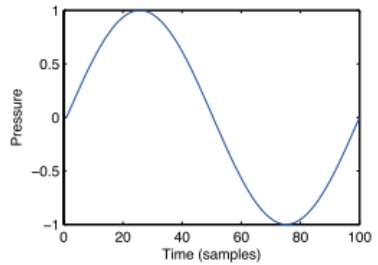
- an offline algorithm is given the whole problem data from the beginning and is required to output an answer which solves the problem at hand.

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

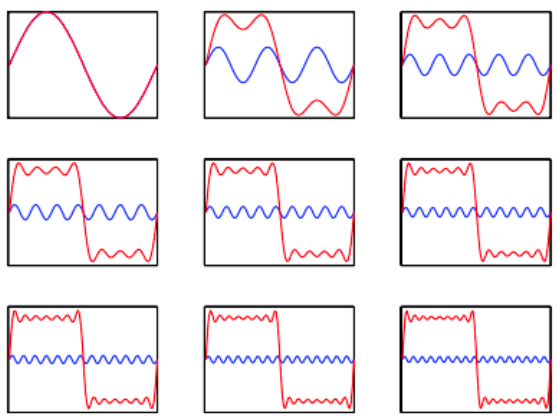
FREQUENCY DOMAIN

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

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

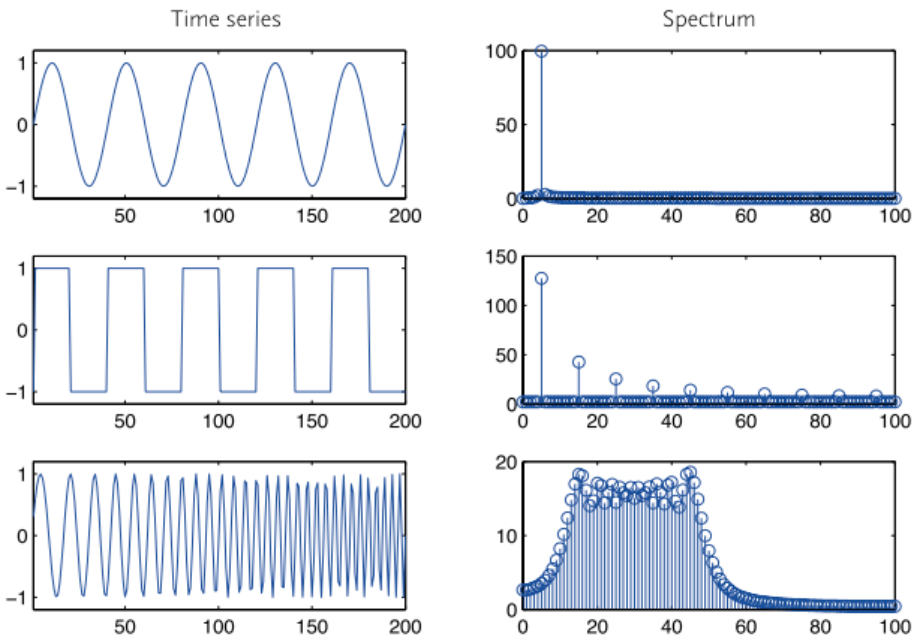


Making a square wave with sines



FREQUENCY SPECTRUM

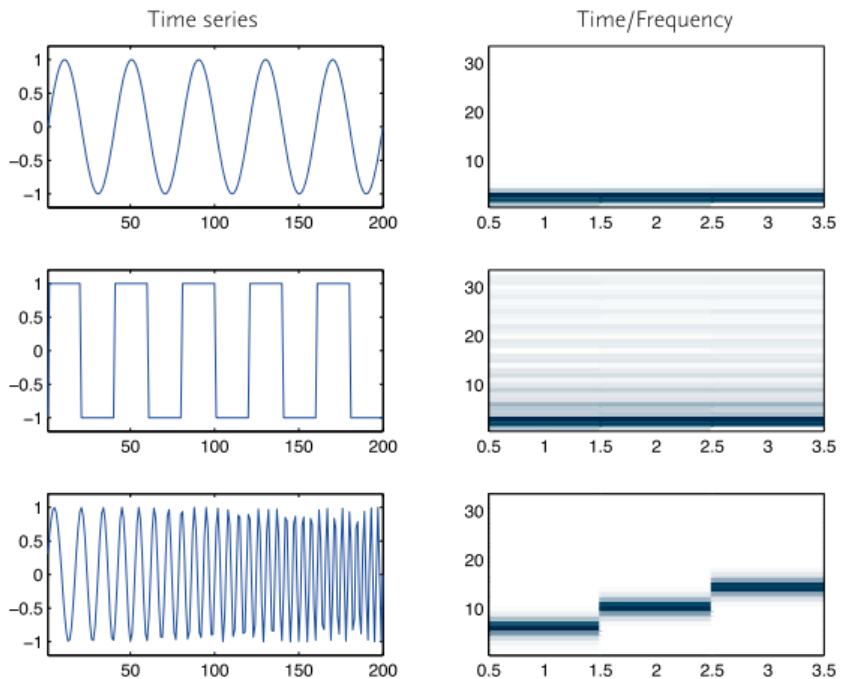
- Time series can be decomposed in terms of “sinusoid presence”
- That’s the frequency spectrum
- No temporal information in this representation, only frequency
- So a signal with changing frequency becomes a smeared spike



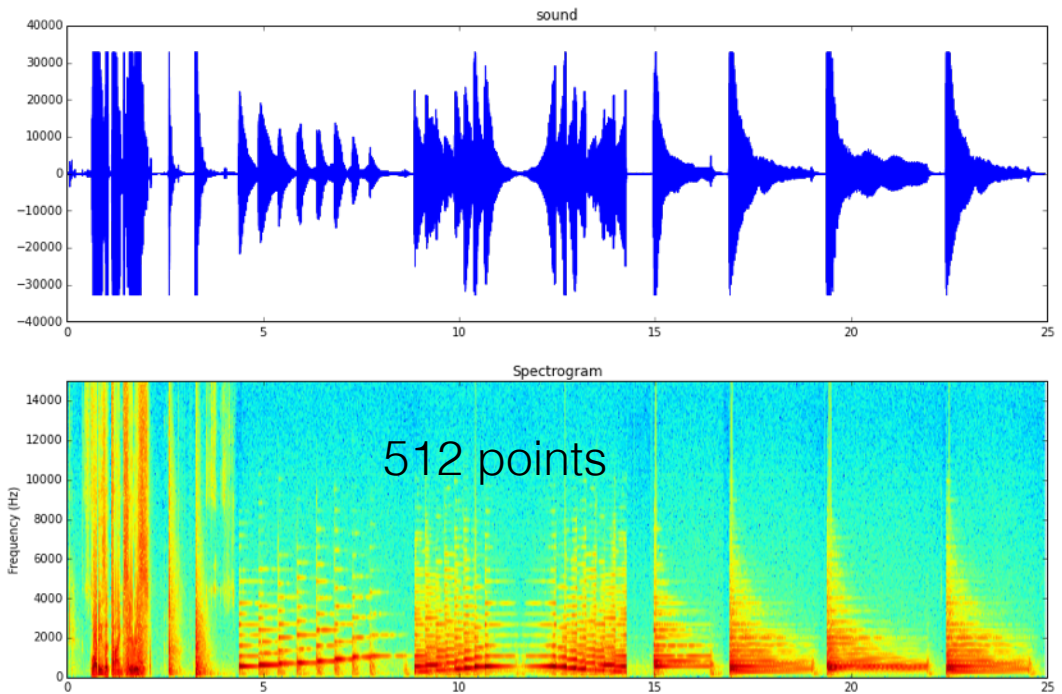
TIME/FREQUENCY REPRESENTATION

- 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!

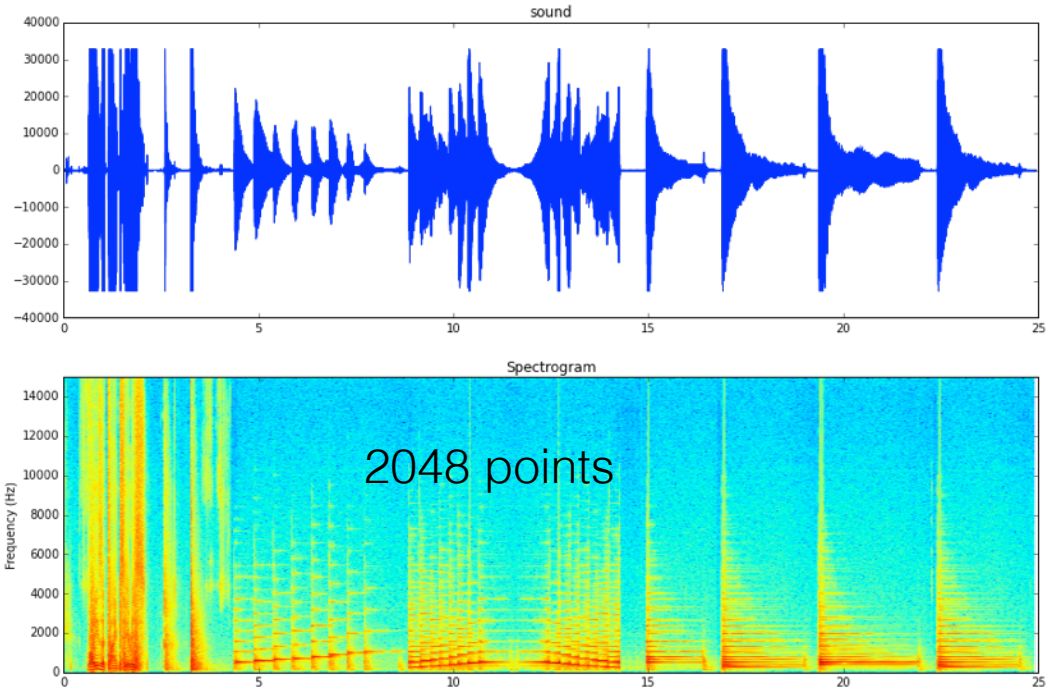
- Harmonics = waves that you can use to recompose periodic signal
- if play guitar, pluck string and it goes up and down. Over time, there's fluctuation up and down, as time moves forward. If finger in middle of string - more frequency, but note is about same.



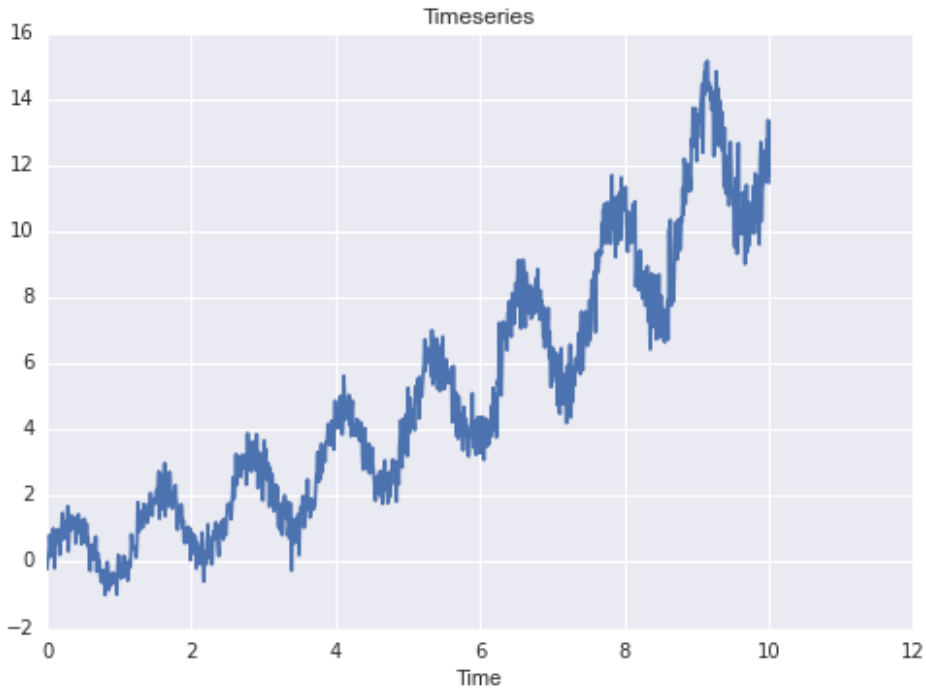
SPECTROGRAM



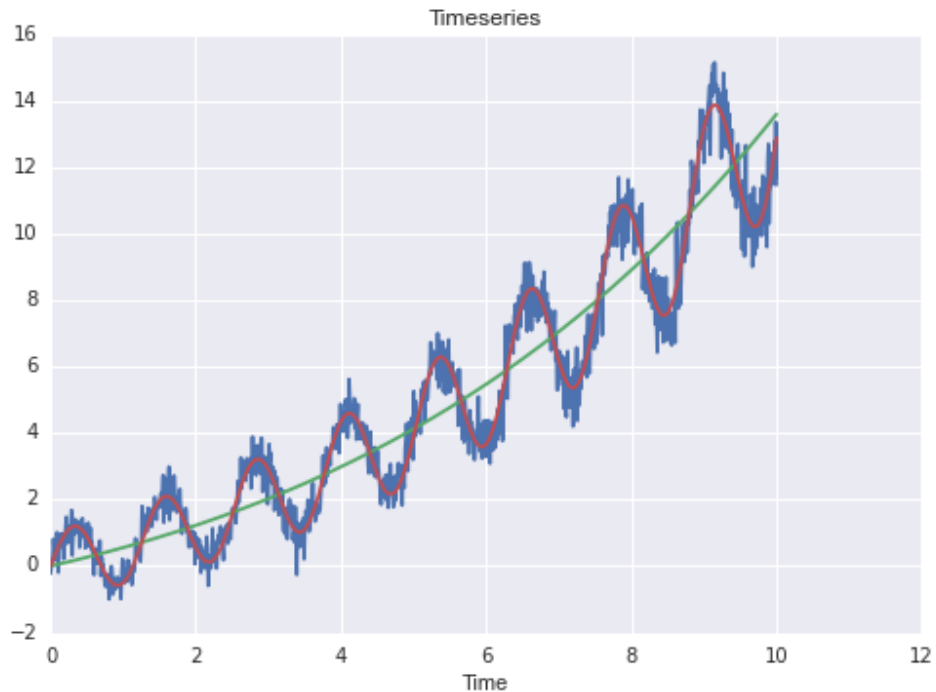
SPECTROGRAM



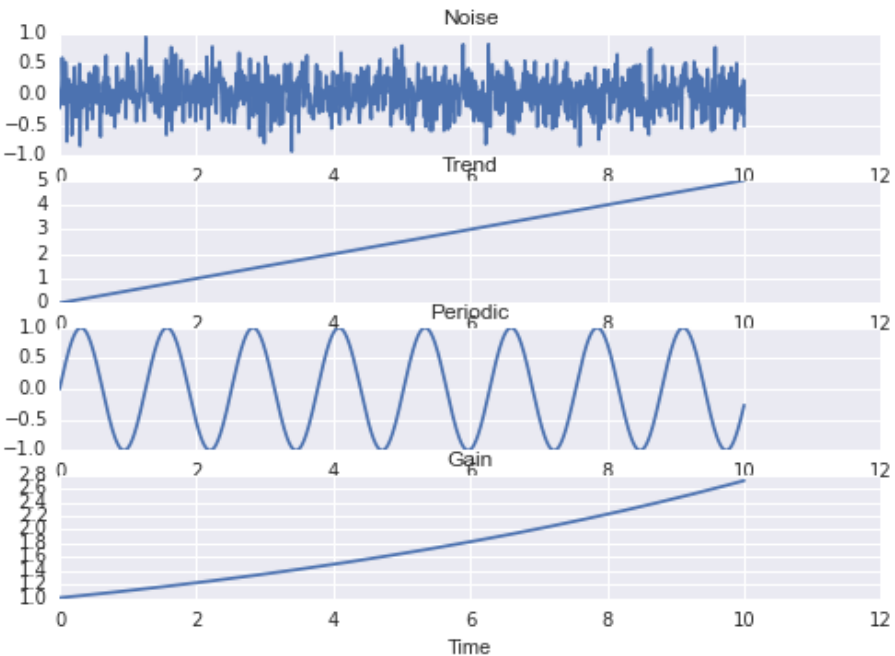
PARAMETRIC OR NOT?



PARAMETRIC OR NOT?



PARAMETRIC OR NOT?



OTHER TOOLS AND TRICKS

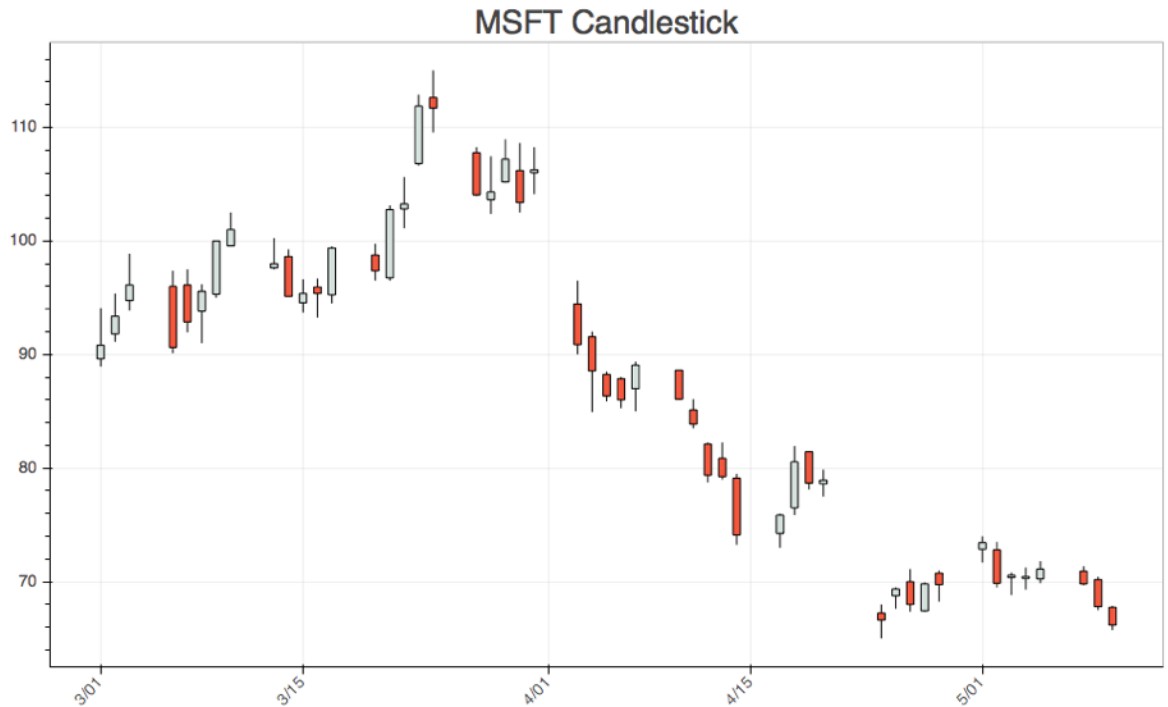
Other Tools & Tricks

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

OTHER TOOLS AND TRICKS

- Candlestick plot
- Lag plot
- Autocorrelation plot
- Time Maps

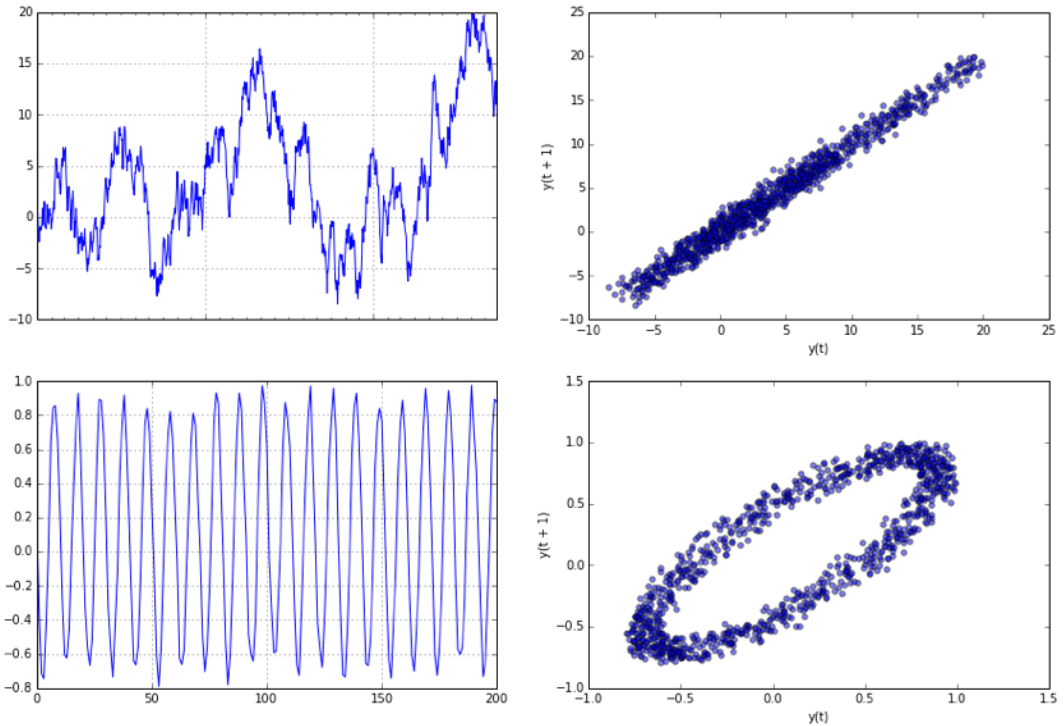
CANDLESTICK PLOT



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

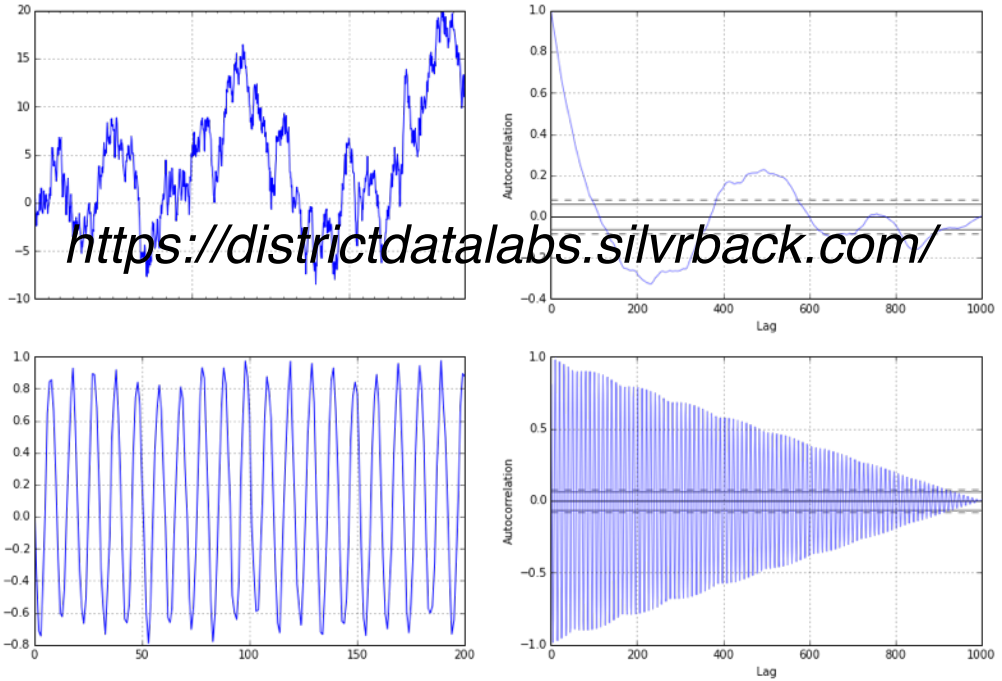
LAG PLOT

plotting pt & next point on scatterplot
if no correlation, see random spread



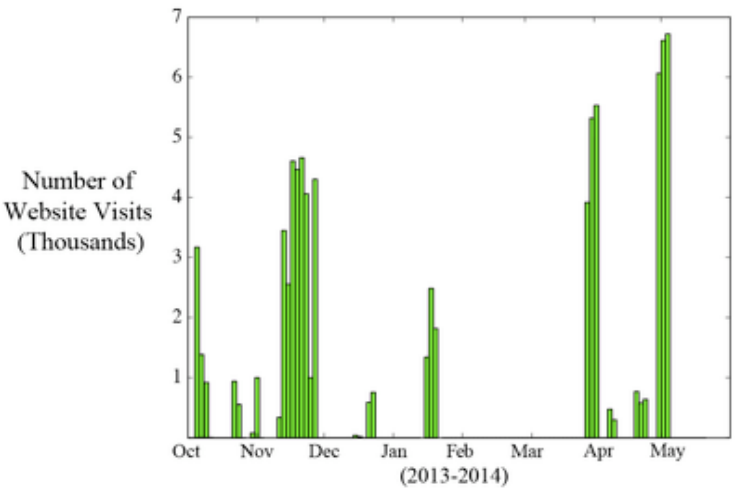
http://pandas.pydata.org/pandas-docs/version/0.15.0/visualization.html#lag-plot

AUTOCORRELATION FUNCTION

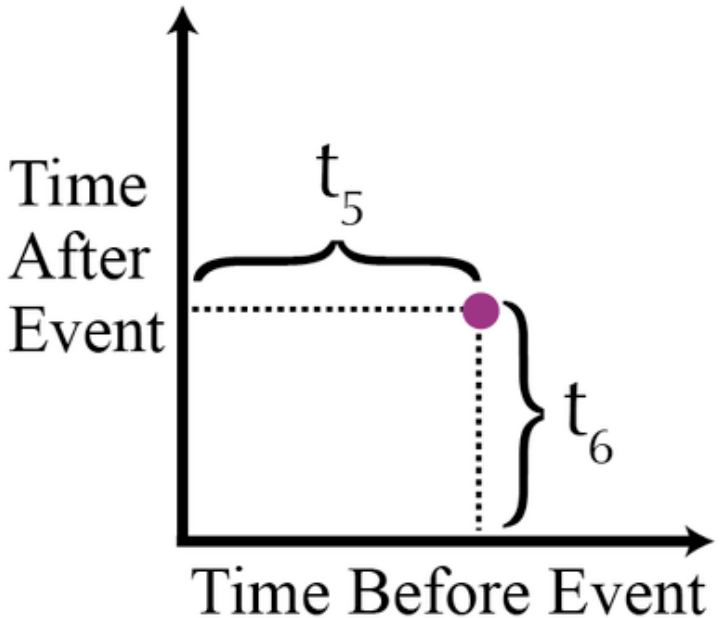


http://pandas.pydata.org/pandas-docs/version/0.15.0/visualization.html#lag-plot

TIME MAPS



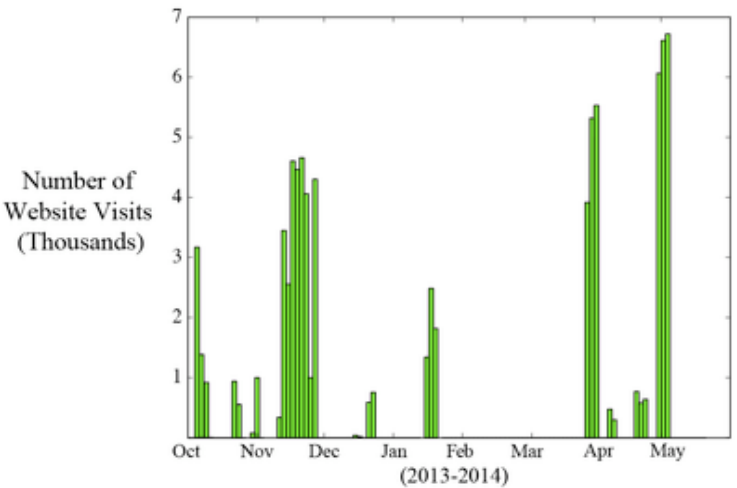
Series of events - cld be # tweets / web pieces. Most time is 0, sometimes hv spikes.

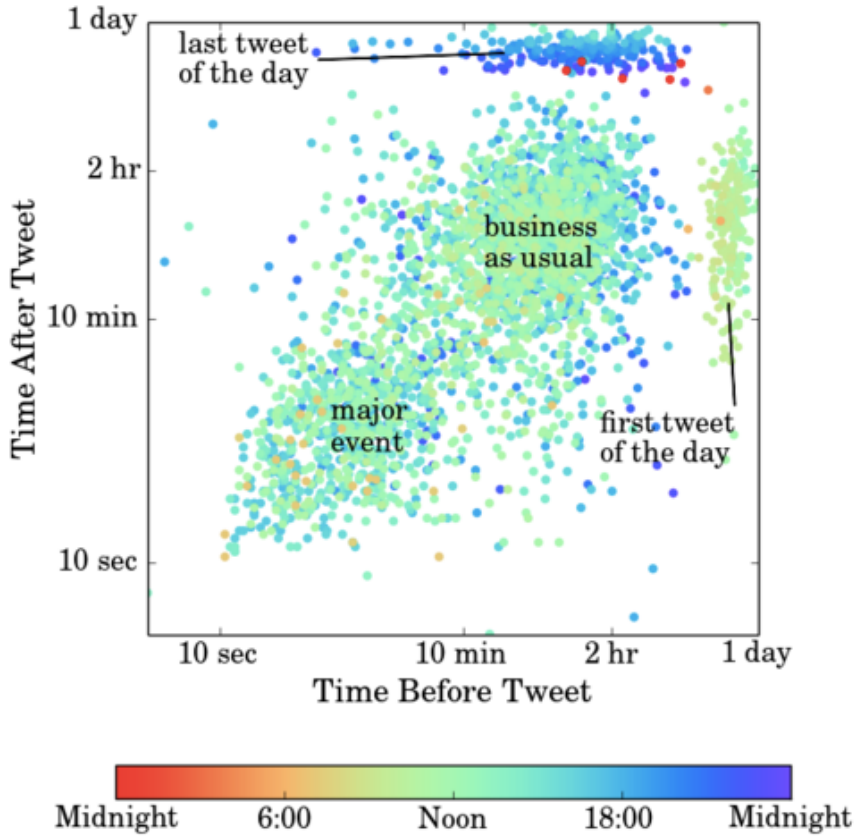


Do a plot where each point has distance from after / before event.

https://districtdatalabs.silvrback.com/time-maps-visualizing-discrete-events-across-many-timescales

TIME MAPS





https://districtdatalabs.silvrback.com/time-maps-visualizing-discrete-events-across-many-timescales

VALIDATION BIAS

- Train - Test split
- Survivor bias
- Labelled data

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.

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

ENGINEERING CHALLENGES

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

REAL WORLD EXAMPLES

REAL WORLD EXAMPLES

RECOGNIZING MOTION PRIMITIVES

Once you've built the offline, can build online
to track movement.
did this by brushingsomeone many times, until sh

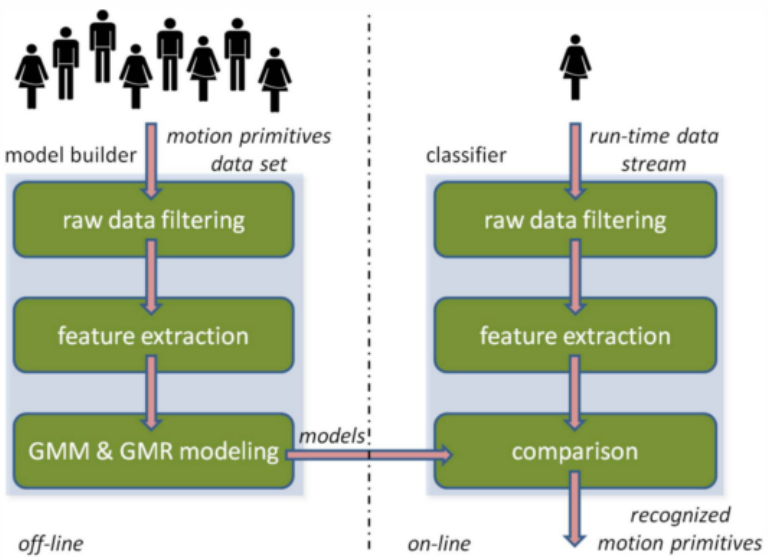


Fig. 1. System architecture.

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

RECOGNIZING MOTION PRIMITIVES

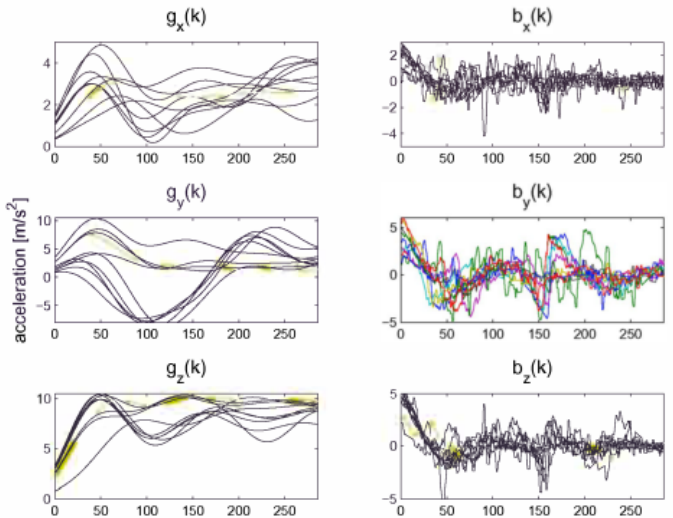


Fig. 2. Feature curves extracted from the trials of the *eating with knife and fork* motion primitive training set.

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

RECOGNIZING MOTION PRIMITIVES

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

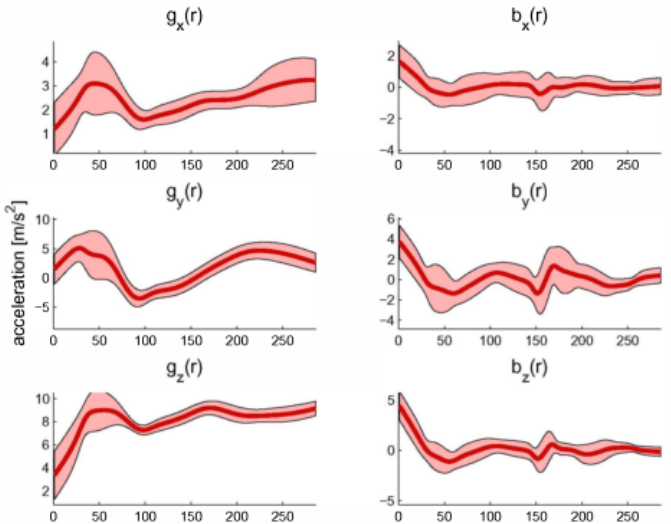
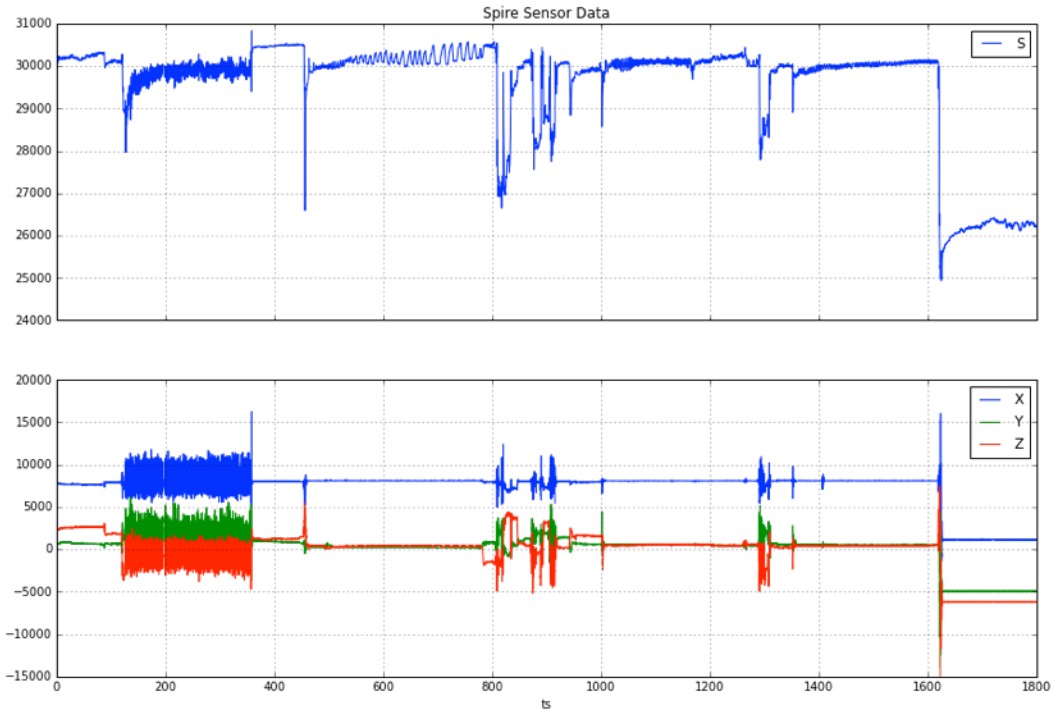


Fig. 3. 2D projections of the *eating with knife and fork* motion primitive model retrieved via GMR.

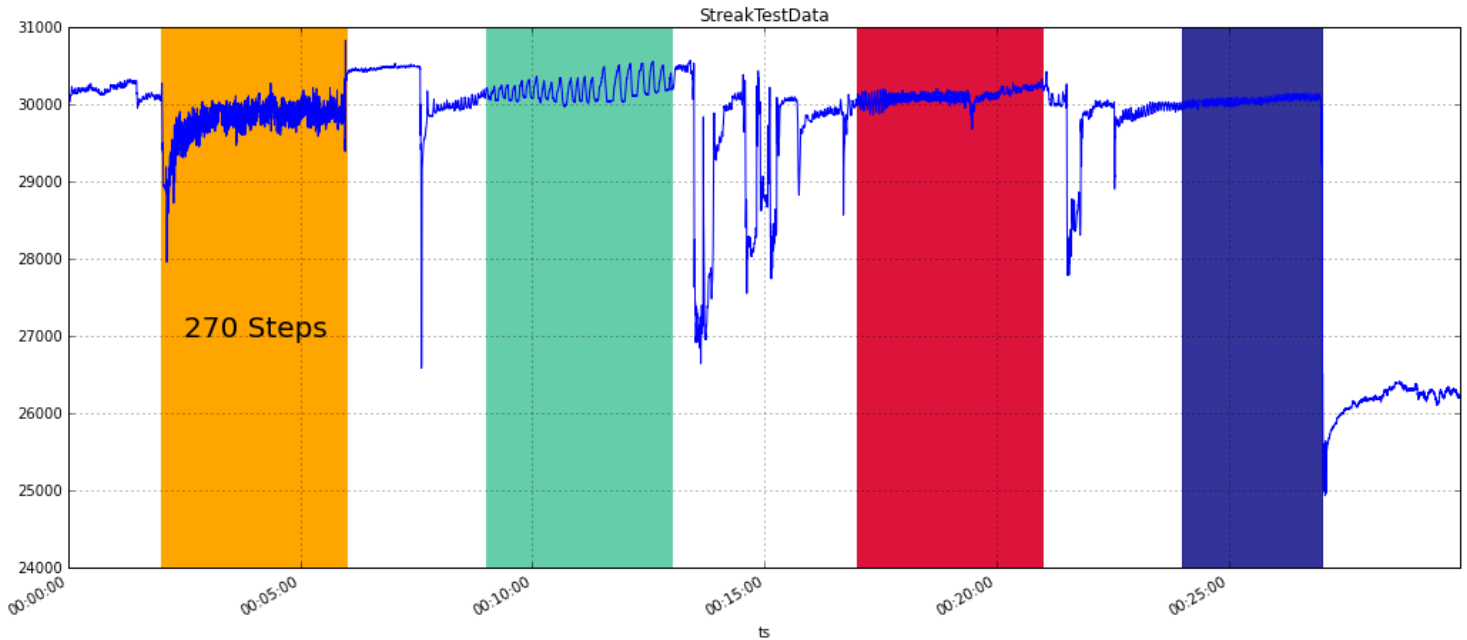
SPIRE



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

DEEP SPEECH

- Recurrent Neural Networks (RNNs)

First step is same as what we've just seen

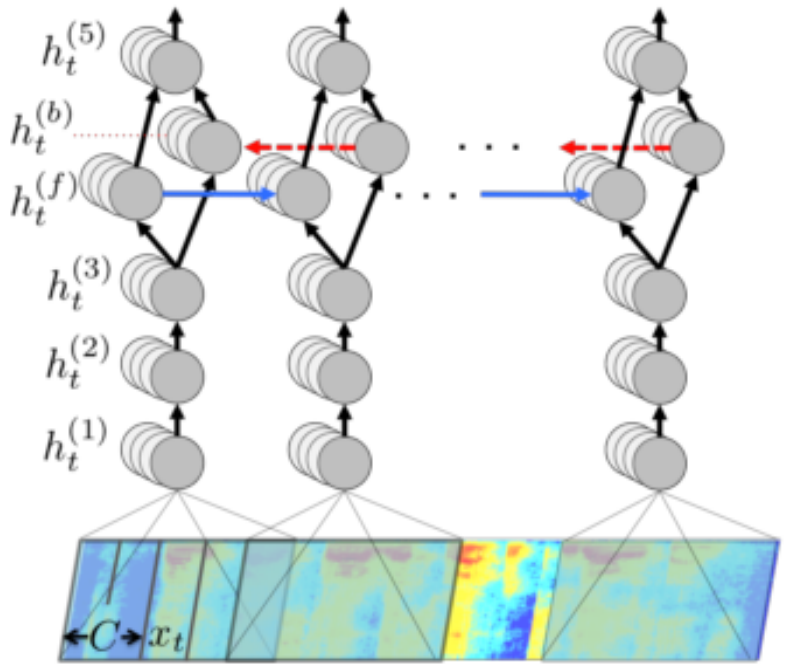


Figure 1: Structure of our RNN model and notation.

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.

arXiv:1412.5567v1

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