





WiML Workshop

Dec 5<sup>th</sup> 2016

Barcelona, Spain

# Learning time series representations through contextualized LSTMs

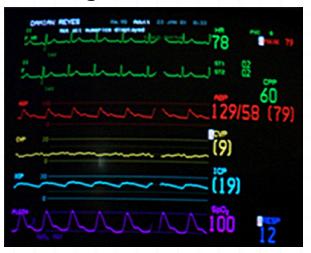
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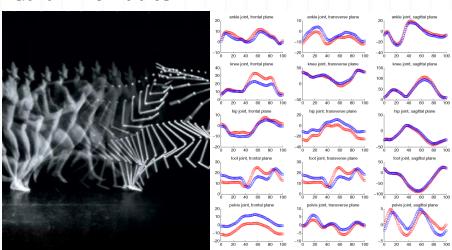
We acknowledge support from the NIH (U54 EB020405).

#### Prevalence of time series data

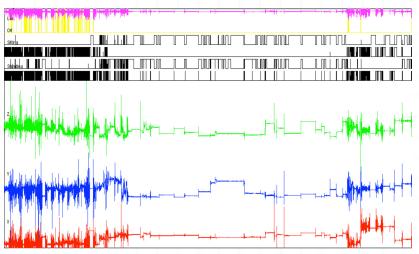
#### Vital Signs



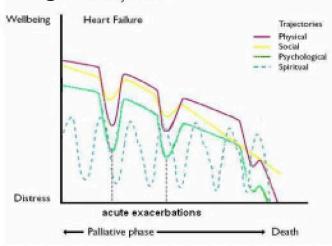
#### **Gait Kinematics**



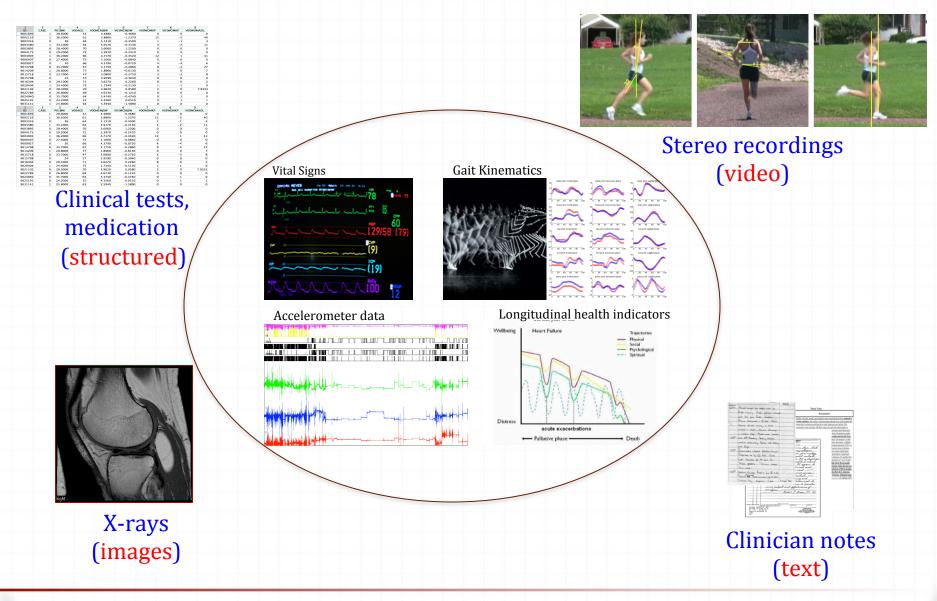
#### Accelerometer data



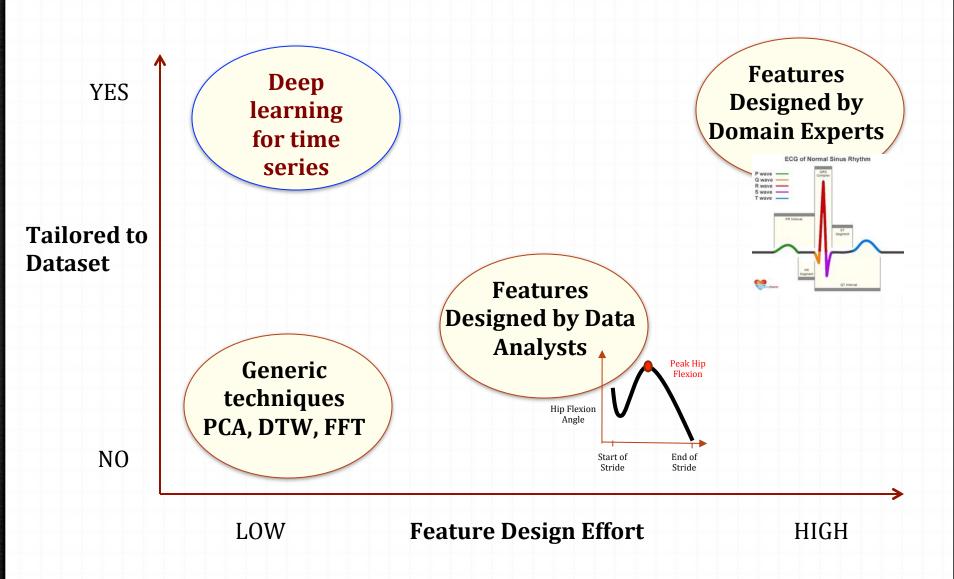
#### Longitudinal health indicators



#### Prevalence of time series data

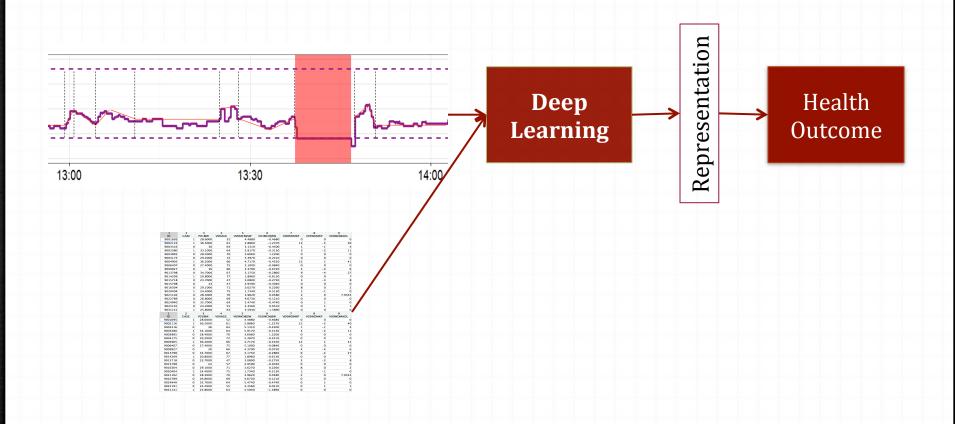


## Learning time series representations

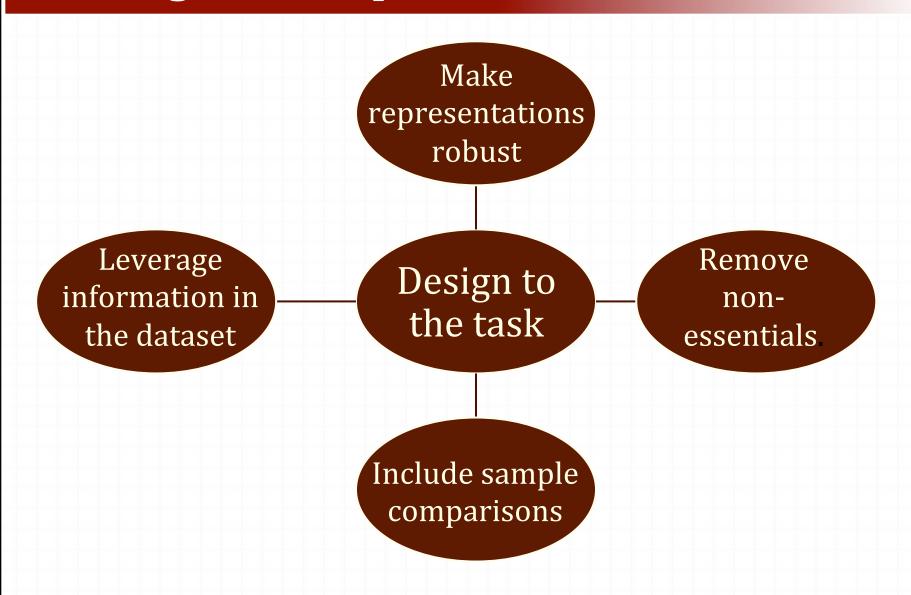


#### Learning setup

Classification or regression of health outcome

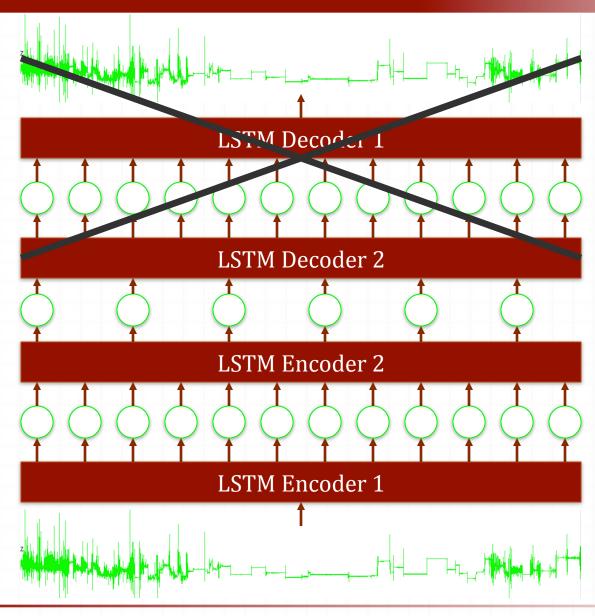


## Learning better representations

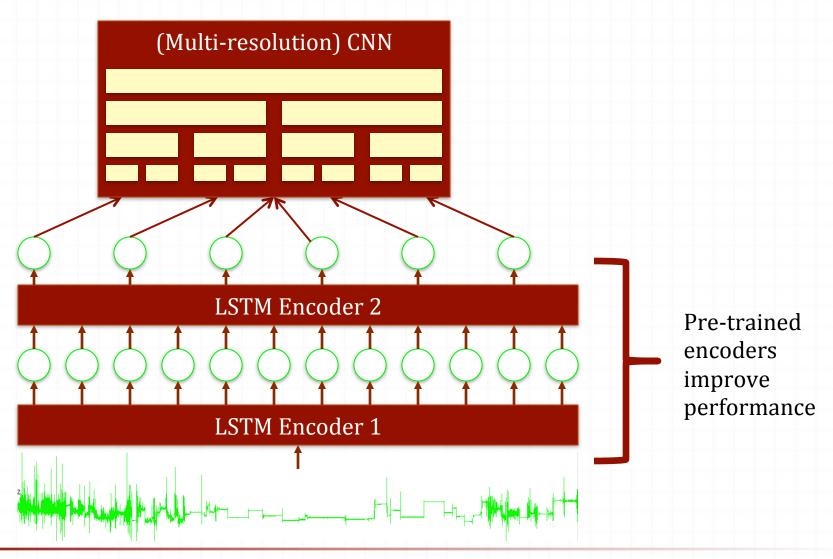




#### Robust models via stacked encoders

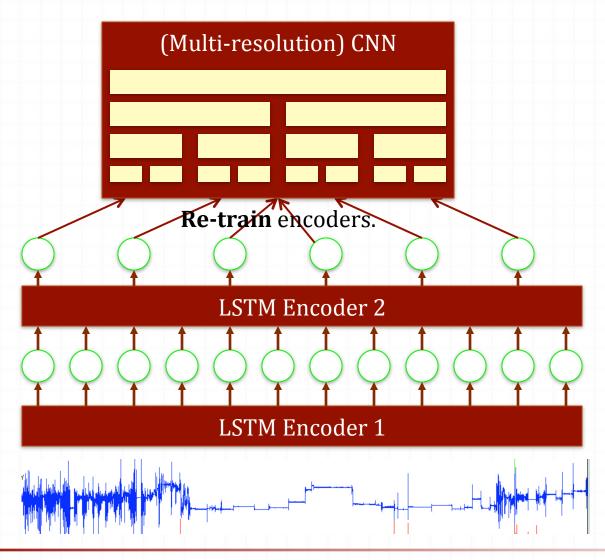


#### Robust models via stacked encoders



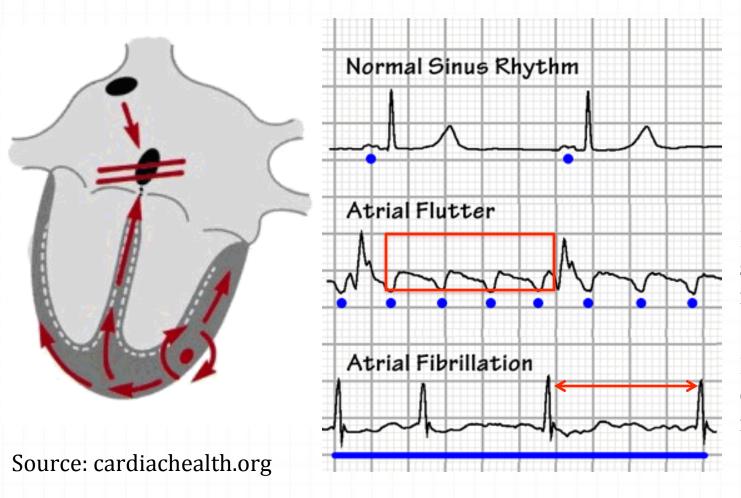
#### Robust models via stacked encoders

**Keep** higher-level logic.



## **Incorporating structured covariates**

Example: how medical history can improve features.

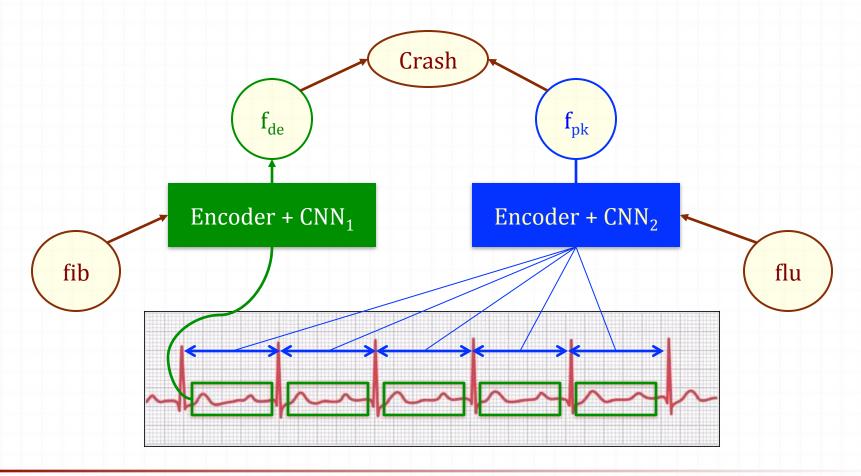


Duty cycle of signal is informative

Peak to peak distance is informative

# **Incorporating structured covariates**

- 2 binary covariates: fibrillation and flutter
- 2 features being learned:  $f_{dc \text{ and }} f_{pk}$ .



## **Incorporating structured covariates**

S = structured covariates

1. Introduce S before the last set of convolutions

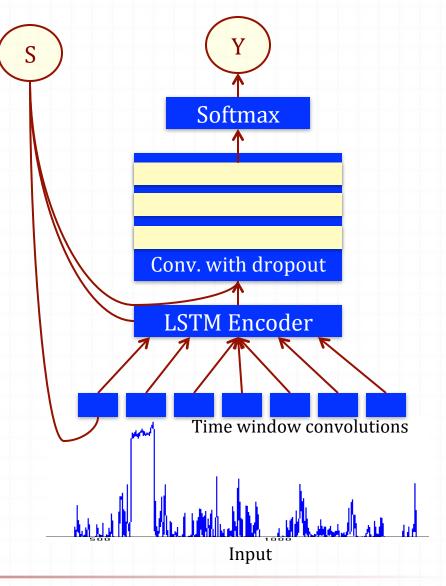
LSTM-C

2. Use S in the LSTM structure
Add terms to nonlinearities of LSTM
W<sub>fs</sub>•s, W<sub>is</sub>•s, W<sub>Cs</sub>•s, W<sub>os</sub>•s

LSTM-S

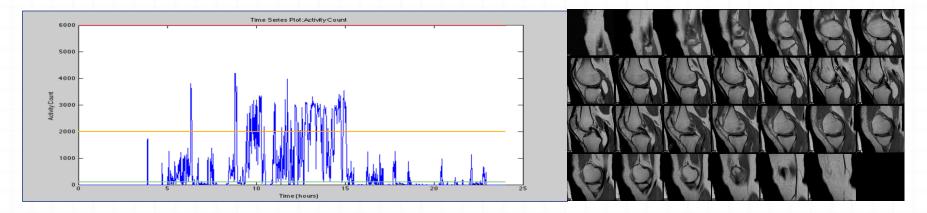
3. Use S as input for time window convolutions

LSTM-TC



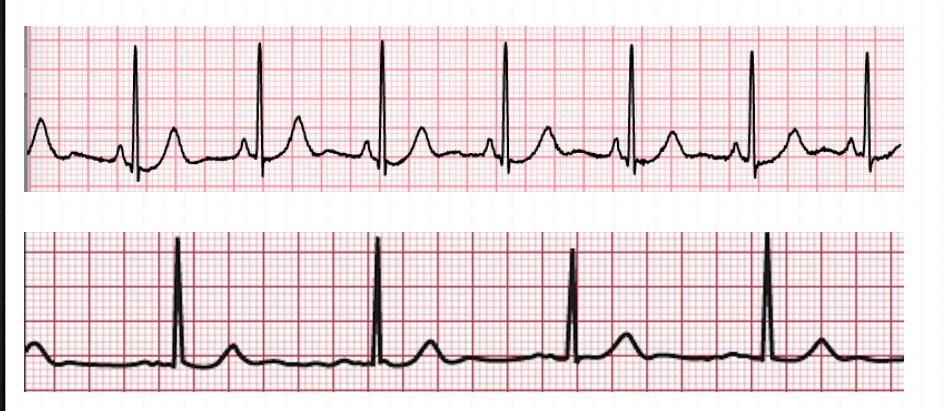
#### Predicting osteoarthritis progression

- Osteoarthritis Initiative Dataset (OAI) accelerometer data obtained from 2000 subjects, for a monitoring period of 7 days, expressed as activity counts; 50 structured covariates.
- Predict whether subjects are at risk for OA-related pain.



Accuracy	Histograms + Rand Forests		LSTM-C	LSTM-S	LSTM-TC
Pain / No pain	0.67	0.68	0.70	0.74	0.73

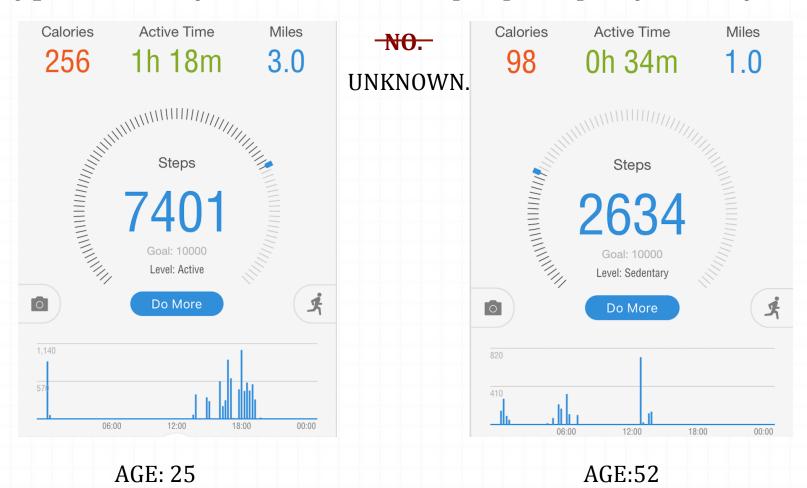
Sinus rhythm. Are these subjects similar?

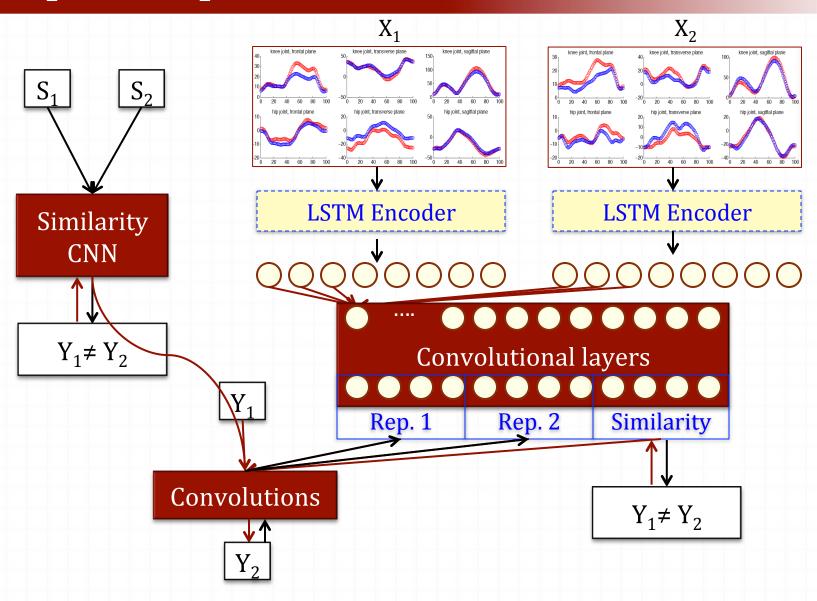


Sinus rhythm. Are these subjects similar?



Typical activity traces. Are these people equally healthy?





## **Similarity LSTM results**

Predicting OA-related pain and cartilage

Method Accuracy	Pain / No pain	Joint space narrowing increase
PCA+SVM	0.67	0.70
LSTM-S	0.74	0.73
LSTM+SIM	0.76	0.73
DTW	0.71	0.71
6-layer CNN	0.68	0.72



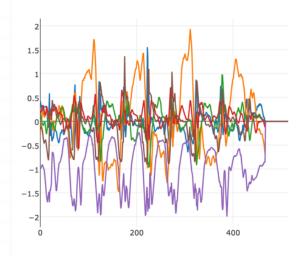
## **Introducing attention**

- Attention allows interpretability of what the network learns
- Can be used to reduce the parameter space
- Sequence is encoded through a bidirectional LSTM
- Last layers: weighted sum of all hidden vectors (attention w)
- Implementation [based on Vinyals 2015]:  $u_i = v^T tanh(Wh_i)$

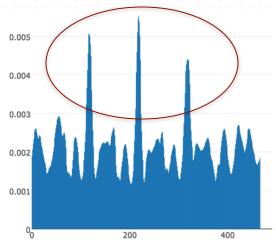
128 Bi-LSTM with sequences Decoder = FC hidden vectors Attention Softmax and layer with 2 of size 100 Encoder Maximum  $(128 \times 1028)$ output classes  $(128 \times 1028 \times$  $(128 \times 200)$  $(128 \times 1)$ x 6)  $(128 \times 2)$ 200)

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## **Introducing attention**

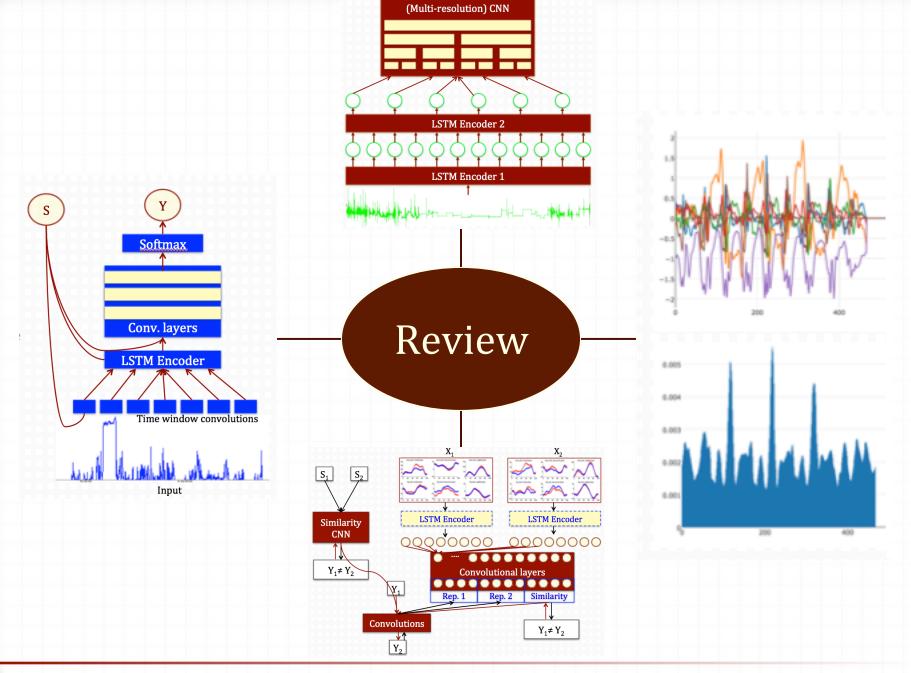


- OU-ISIR Gait Database, 1280 sequences
- 6 times series per patient: triaxial accelerometer/gyroscope
- Classify whether subject as male/female
- Prediction accuracy: 83%



#### Future work:

- Improve the model architecture (replace RNNs with CNNs)
- Compute separate attention weights for each dimension of the input







# Thanks!

We acknowledge support from the NIH (U54 EB020405). We thank Dr. Eni Halilaj for her contributions to the Osteoarthritis Progression experiment.



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