Biomedical Time Series Representations in the Presence of Structured Information

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Machine Learning in Healthcare
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mobilize

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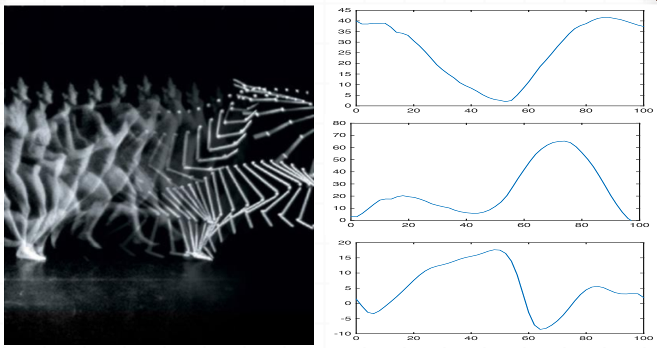
Time series

Gait kinematics



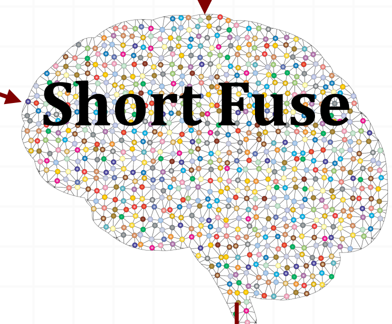
Longitudinal data

Accelerometry

Vital signs

Structured information

Demographics
Clinical tests
Medical history



Representations

Prediction

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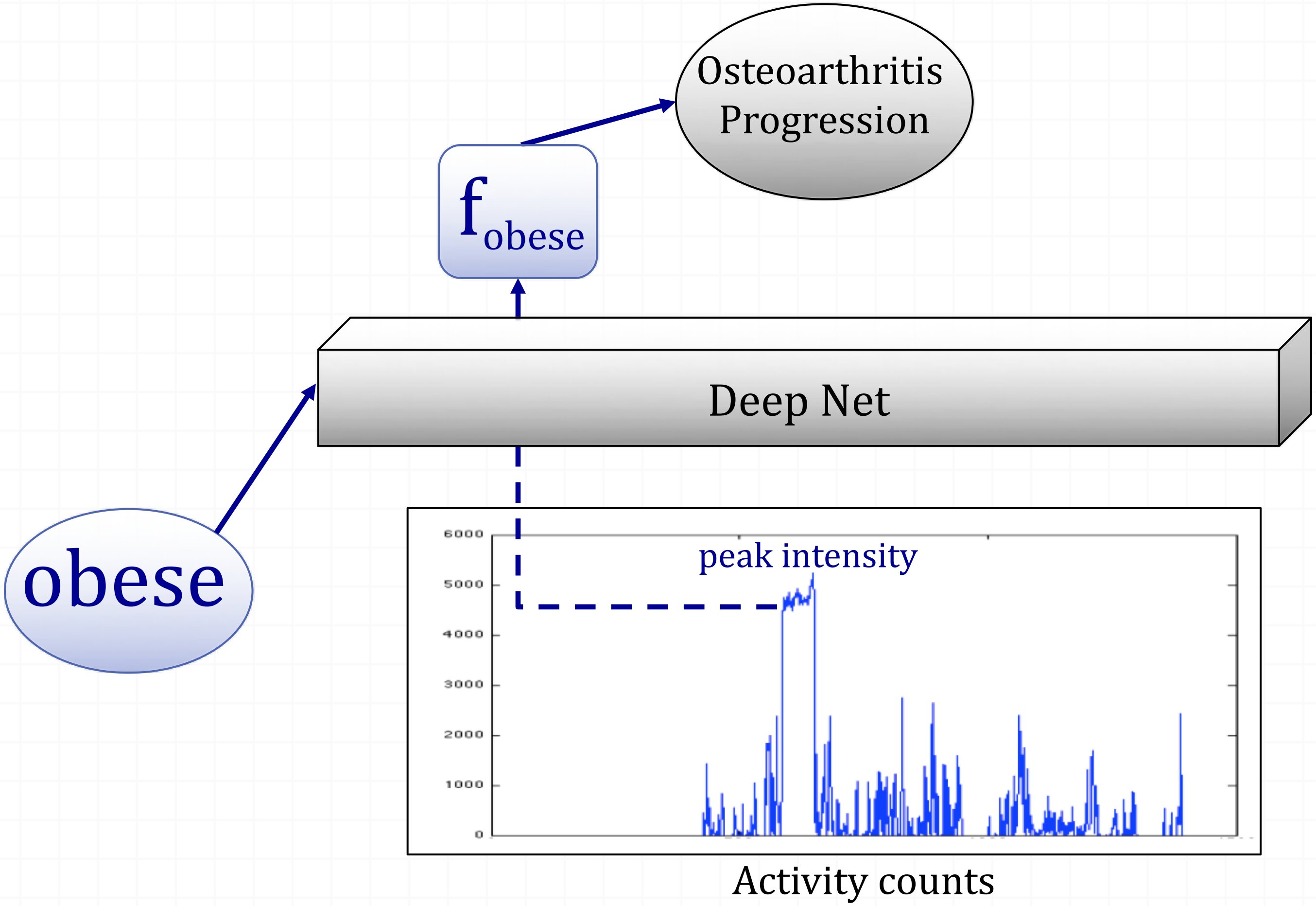

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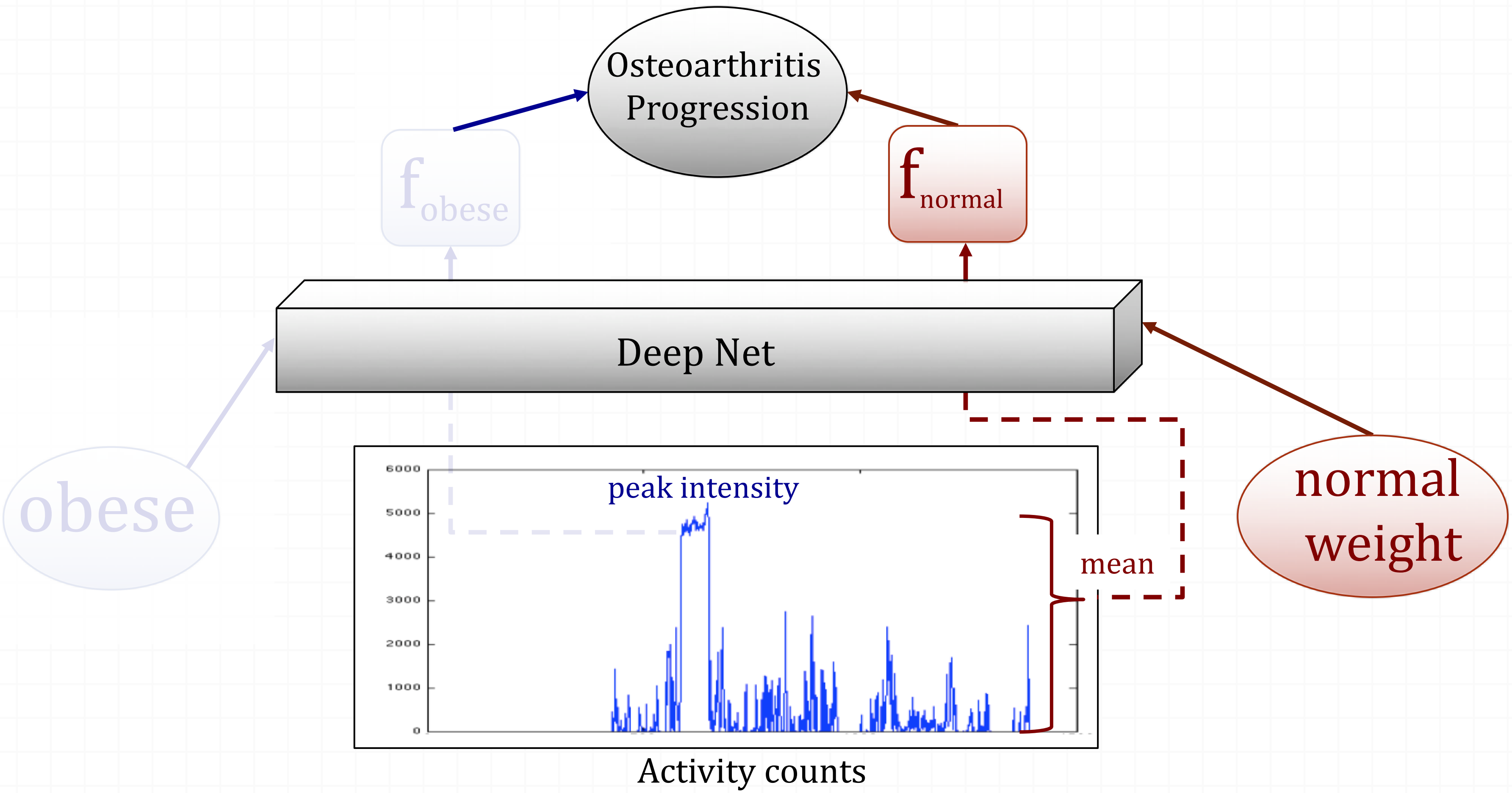

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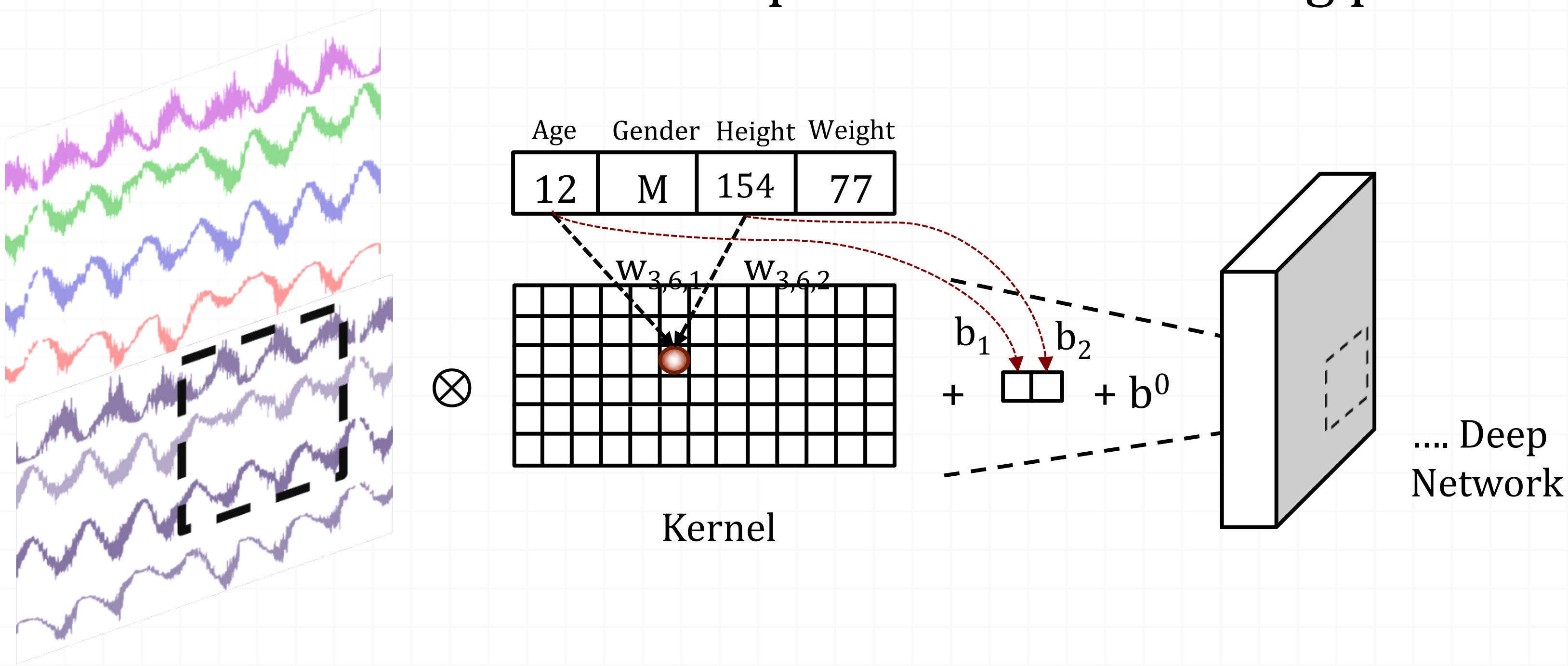
Covariates introduced in the representation learning process



- **Hybrid convolutions**
- Each filter uses a different set of covariates

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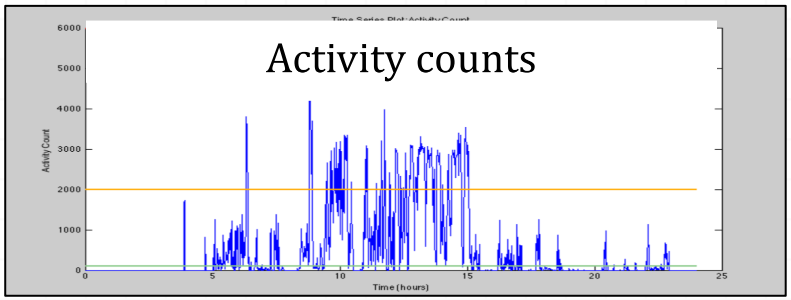
Forecasting the speed of **osteoarthritis progression**

Joint symptoms , Medical history,
Nutrition, Physical exams.

+

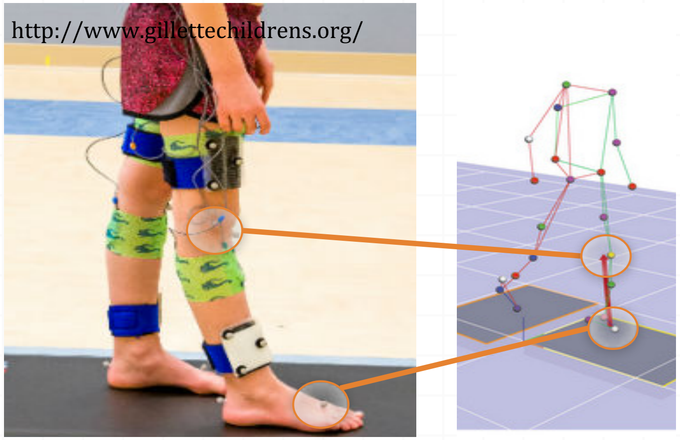


Binary classification: **fast/slow**

State of the art: **67%** accuracy

ShortFuse: **74%** accuracy

Predicting **surgery outcome** for children with cerebral palsy



Classification: **good/bad** outcome

Baseline: 78% (domain expertise)

ShortFuse: 78% no feature engineering