Collecting, Modeling and Predicting Human Gait Kinematics

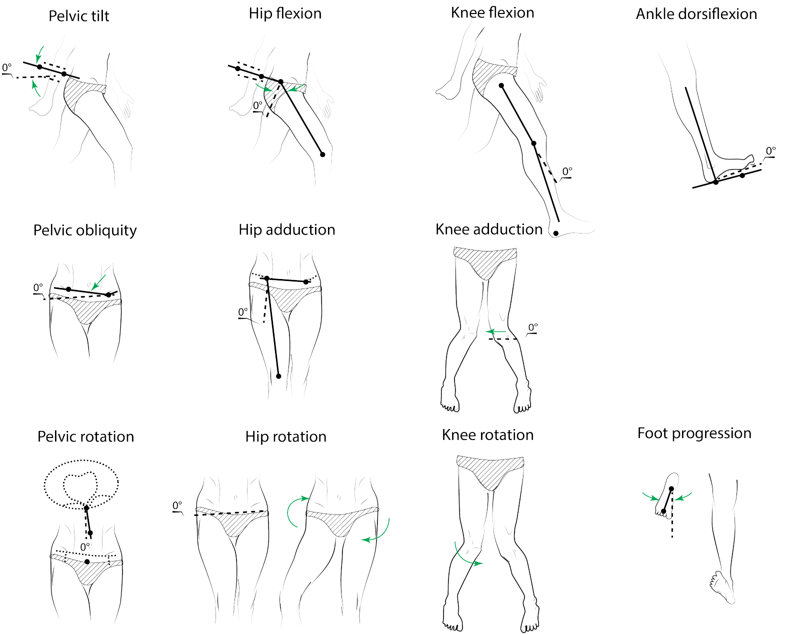
Łukasz Kidziński

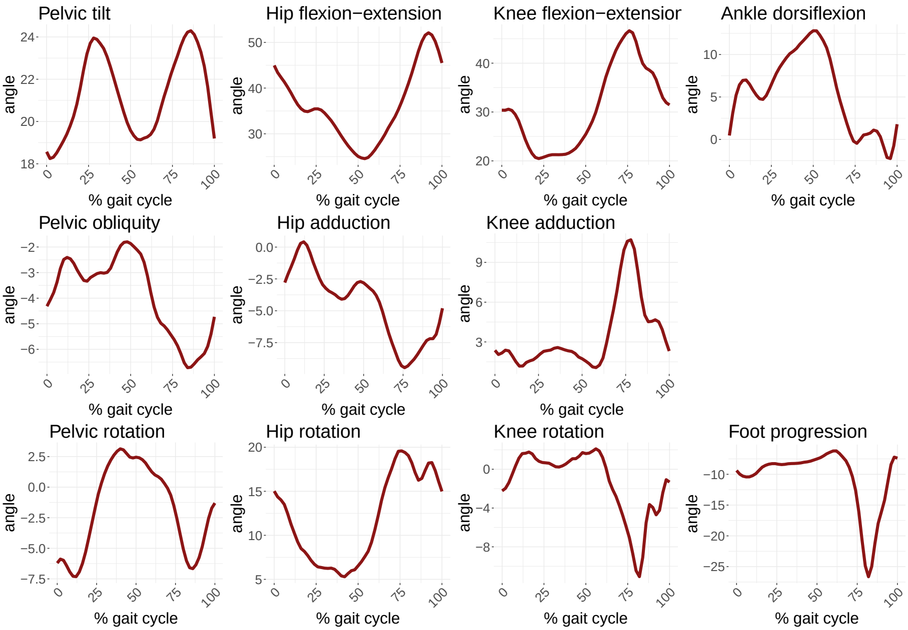
Stanford University

June 12, 2018


Collecting
Modeling
Predicting

Collecting kinematic data


Pelvic tilt
0°
Hip flexion
0°
Knee flexion
0°
Ankle dorsiflexion
0°
Pelvic obliquity
0°
Hip adduction
0°
Knee adduction
0°
Pelvic rotation
0°
Hip rotation
0°
Knee rotation
Foot progression


Pelvic tilt
24
22
20
18
angle
0 25 50 75 100
% gait cycle
Hip flexion−extension
50
40
30
angle
0 25 50 75 100
% gait cycle
Knee flexion−extensior
40
30
20
angle
0 25 50 75 100
% gait cycle
Ankle dorsiflexion
10
5
0
angle
0 25 50 75 100
% gait cycle
Pelvic obliquity
−2
−3
−4
−5
−6
angle
0 25 50 75 100
% gait cycle
Hip adduction
0.0
−2.5
−5.0
−7.5
angle
0 25 50 75 100
% gait cycle
Knee adduction
9
6
3
angle
0 25 50 75 100
% gait cycle
Pelvic rotation
2.5
0.0
−2.5
−5.0
−7.5
angle
0 25 50 75 100
% gait cycle
Hip rotation
20
15
10
5
angle
0 25 50 75 100
% gait cycle
Knee rotation
0
−4
−8
angle
0 25 50 75 100
% gait cycle
Foot progression
−10
−15
−20
−25
angle
0 25 50 75 100
% gait cycle

Cons

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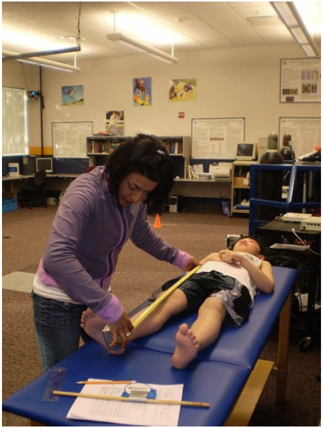
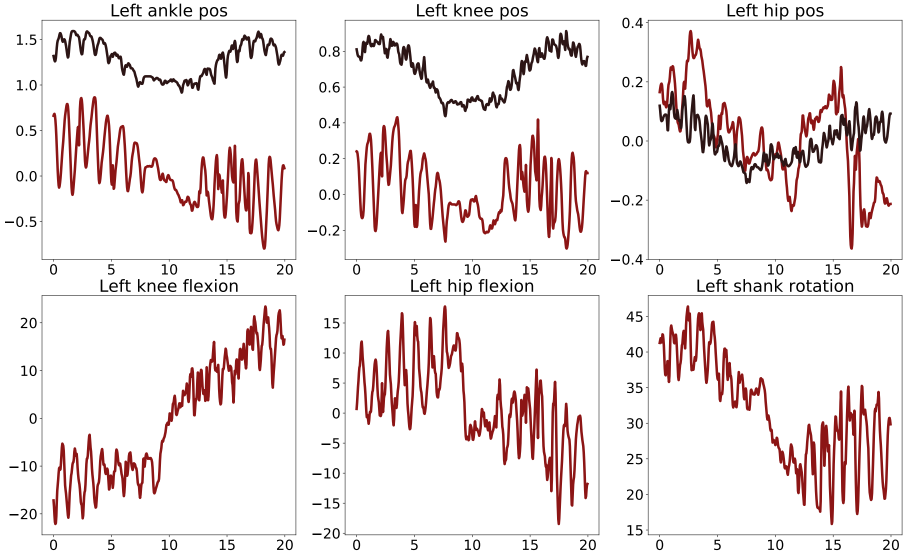


Problems:

- Expensive equipment
- An engineer needed
- A physical therapist needed
- Controlled lab environment

Therefore:

- Only a few visits in patient's life
- Function different outside of the lab


Left ankle pos
Left knee pos
Left hip pos
Left knee flexion
Left hip flexion
Left shank rotation

Getting the cadence

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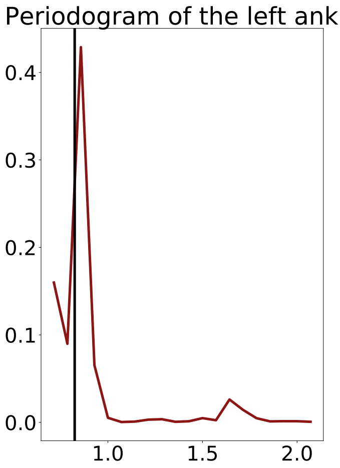

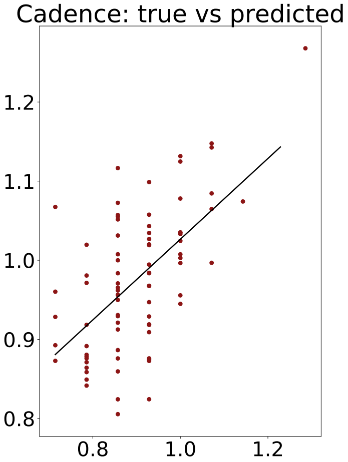

$$\rho = 0.6$$

Getting the step length

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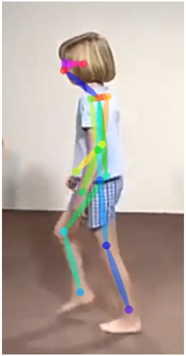
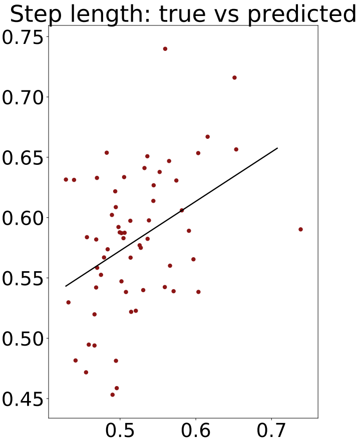




$$\hat{S} = 1.2H \cdot \frac{max_t |x_{ank,L}(t) - x_{ank,R}(t)|}{max_t |y_{ear,L}(t) - y_{ank,L}(t)|},$$

$$\rho = 0.41$$

Getting the GDI

Knee flexion

Hip extension

Variances

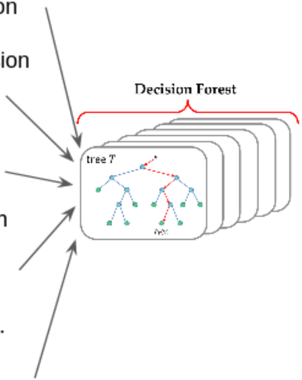
Speed

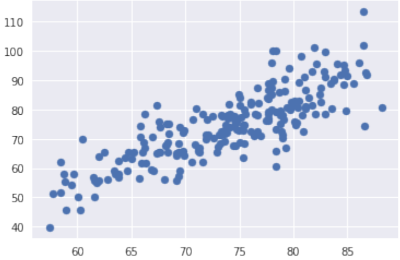
Step length

Cadence

Knees dist.

...



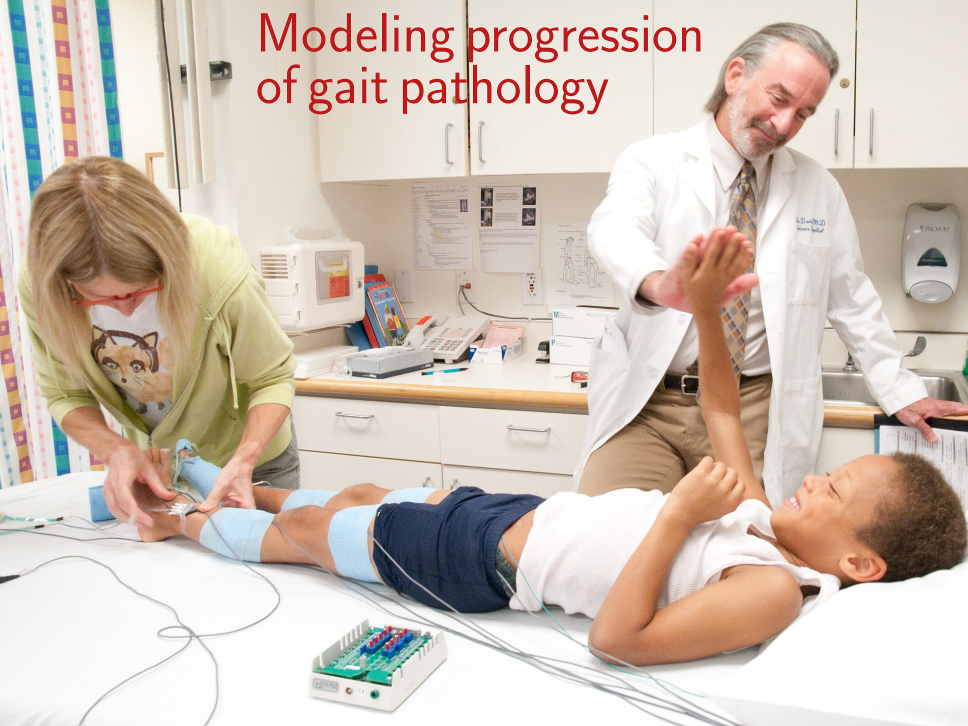


$$\rho = 0.82$$

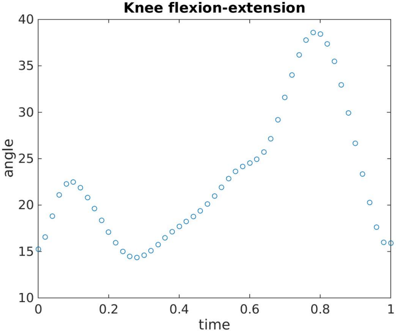
Objective:

A library for extracting meaningful biomechanic signals from videos

Modeling progression of gait pathology



Dataset - Functional features



Dimensionality reduction

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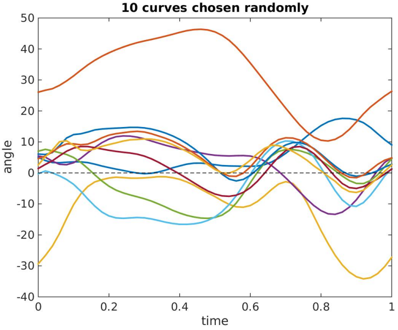
1. We reduce dimensionality using PCA.



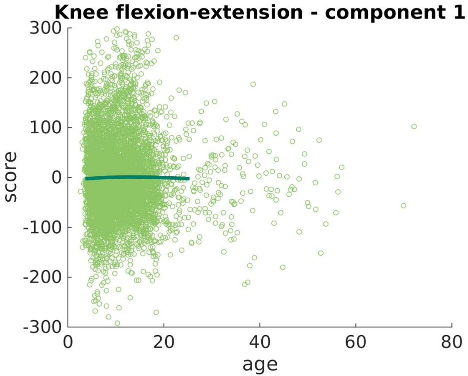
age	PC1	PC2	PC3
5.8	33.5	−12.4	43.7
5.0	233.3	34.7	−25.4
6.9	−77.4	49.4	−67.1
9.4	29.3	8.2	−42.7
10.7	−26.2	1.8	31.6
6.3	−55.8	18.7	31.3
10.0	9.5	10.4	4.0
13.0	51.4	14.0	−4.6
5.9	47.4	18.0	0.4
9.8	35.9	21.1	−11.6
⋮	⋮	⋮	

Modelling

Stanford University

2. We model each component as a function of age.

age	PC1	PC2	PC3
5.8	33.5		
5.0	233.3		
6.9	−77.4		
9.4	29.3		
10.7	−26.2		
6.3	−55.8		
10.0	9.5		
13.0	51.4		
5.9	47.4		
9.8	35.9		
⋮	⋮		



Modelling

Stanford University

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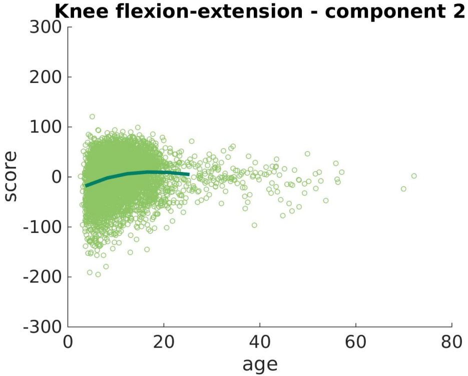
6.9		49.4	
9.4		8.2	
10.7		1.8	
6.3		18.7	
10.0		10.4	
13.0		14.0	
5.9		18.0	
9.8		21.1	
⋮		⋮	



Modelling

Stanford University

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age	PC1	PC2	PC3
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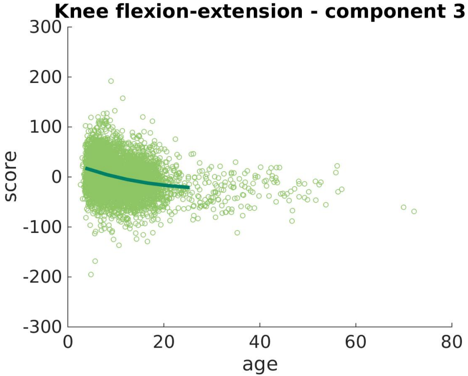
6.9			−67.1
9.4			−42.7
10.7			31.6
6.3			31.3
10.0			4.0
13.0			−4.6
5.9			0.4
9.8			−11.6
⋮			⋮



Modelling

Stanford University

3. We reconstruct the process.

age	PC1	PC2	PC3
4.08	0.49	−4.47	10.21
4.16	0.48	−4.42	10.09
4.24	0.48	−4.37	9.97
4.32	0.47	−4.32	9.85
4.40	0.46	−4.26	9.73
4.48	0.46	−4.21	9.61
4.56	0.45	−4.16	9.49
4.64	0.45	−4.11	9.38
4.72	0.44	−4.06	9.26
4.80	0.44	−4.00	9.14
⋮	⋮	⋮	⋮

Individual evolutions

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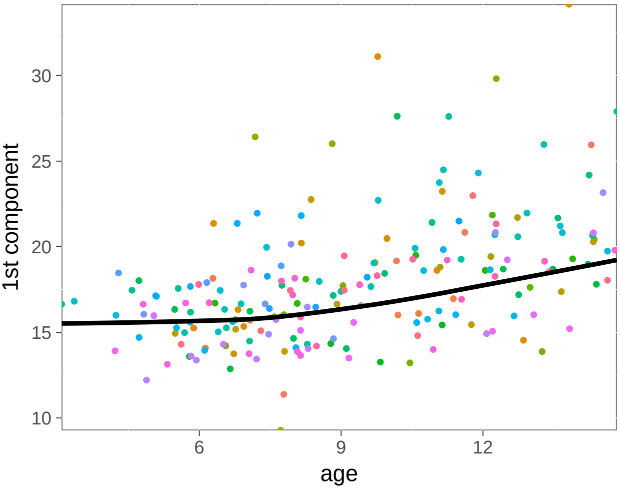
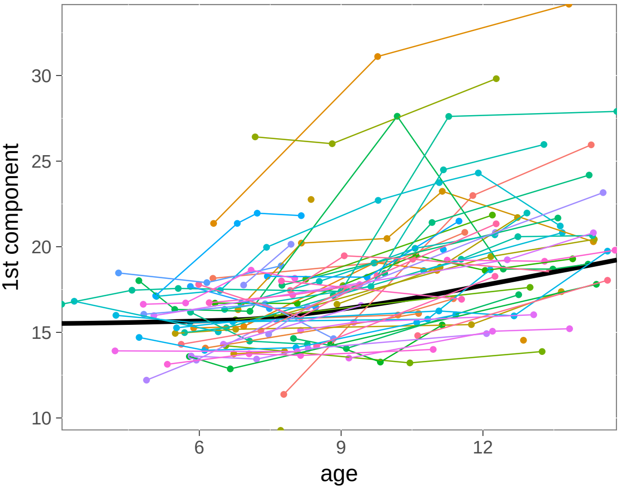


Individual evolutions

Stanford University



Problem

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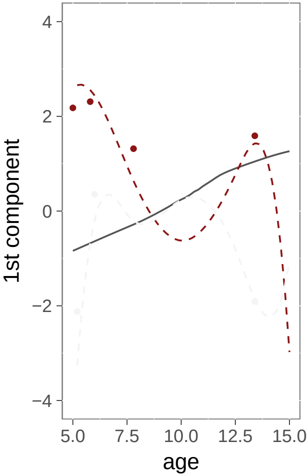
Data:

For each patient $i \in \{1, ..., N\}$, observe n_i points $\{y_{i,1}, y_{i,2}, ..., y_{i,n_i}\}$ at age $\{t_{i,1}, t_{i,2}, ..., t_{i,n_i}\}$.

Problem:

Estimate individual curves $Y_i(t)$.



Problem

Stanford University

Data:
For each patient $i \in \{1, ..., N\}$,
observe n_i points $\{y_{i,1}, y_{i,2}, ..., y_{i,n_i}\}$
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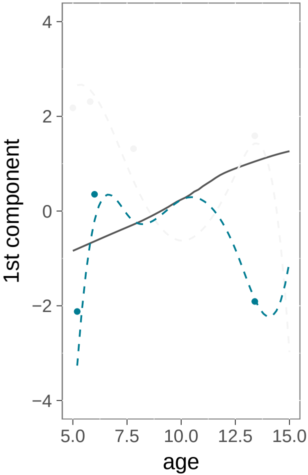

Solution 1: Mixed-effect model

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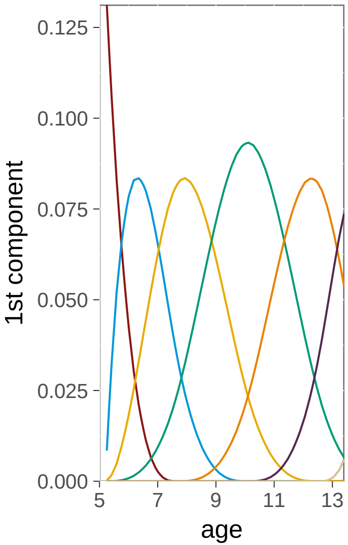
We assume

$$y_{i,\cdot} \sim \mathcal{N}(\mu_i + B_i \mathbf{w}_i, \sigma^2 I_{n_i}),$$

where $\mathbf{w}_i \sim \mathcal{N}(0, \Sigma)$, $\Sigma \in \mathbb{R}^{K \times K}$.



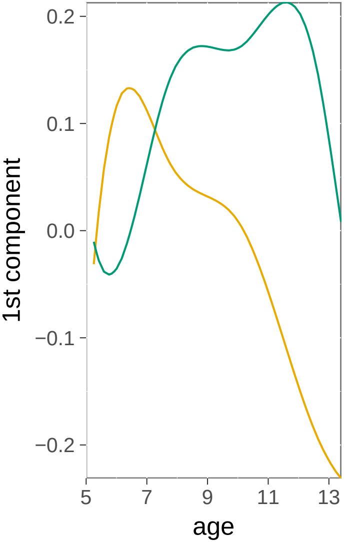
Solution 2: Low-rank model

Stanford University

We assume

$$y_{i,\cdot} \sim \mathcal{N}(\mu_i + B_i A \mathbf{w}_i, \sigma^2 I_{n_i}),$$

where $\mathbf{w}_i \sim \mathcal{N}(0, \Sigma)$, $\Sigma \in \mathbb{R}^{D \times D}$, $A \in \mathbb{R}^{K \times D}$ and $D < K$.



Solution 3: Matrix completion

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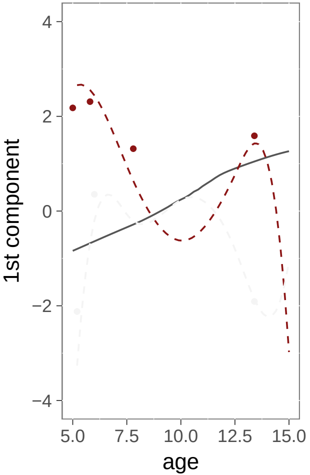
We want to fit

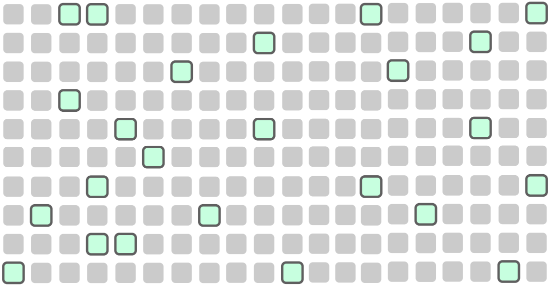
$$\sum_{i=1}^{N}\sum_{j=1}^{n_i}\|Y_i(t_{i,j}) - y_{i,j}\|^2$$



Solution 3: Matrix completion

Stanford University

Y



Ω - set of observed indices

$P_\Omega(\cdot)$ - projection on observed subspace

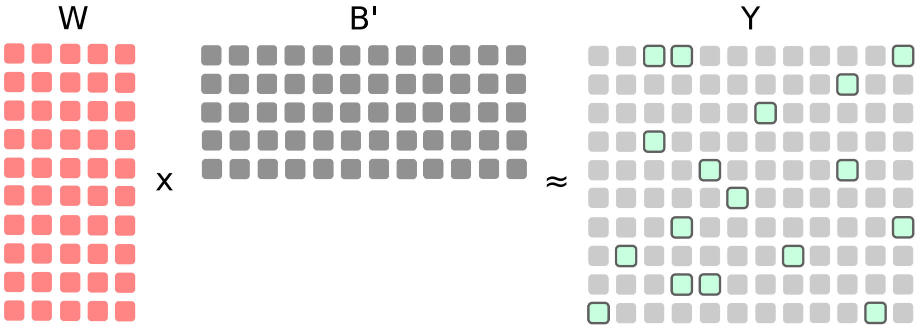
$\|A\|_F^2$ - sum of squared elements

$\|A\|_*$ - sum of singular values

Solution 3: Matrix completion

Stanford University

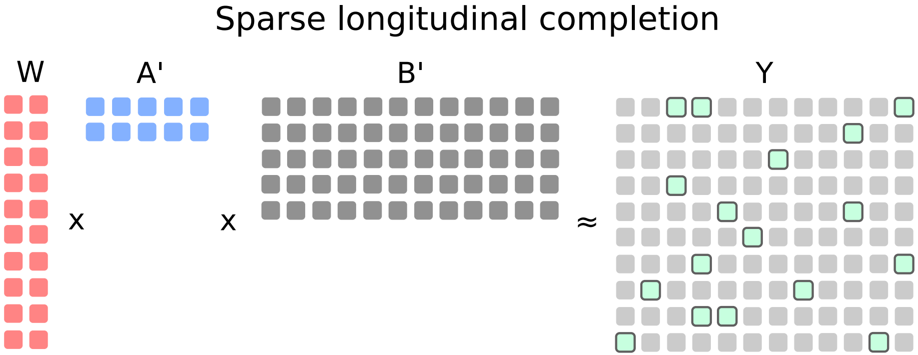
Mixed-effect model



$$\underset{W}{\arg\min} \|P_\Omega(WB' - Y)\|_F^2$$

Solution 3: Matrix completion

Stanford University

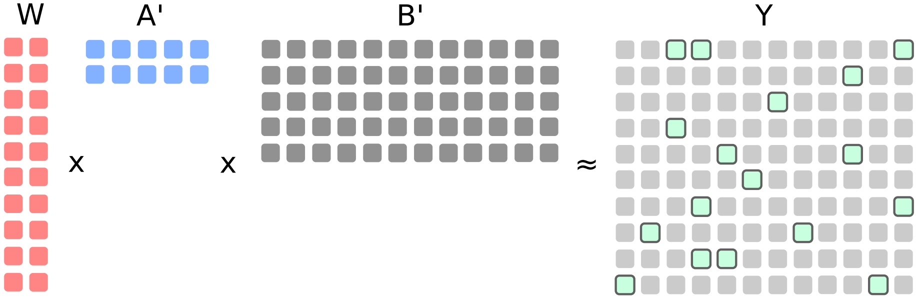


$$\underset{W,A}{\arg\min} \| P_\Omega (W A' B' - Y) \|_F^2$$

Solution 3: Matrix completion

Stanford University

Sparse longitudinal completion

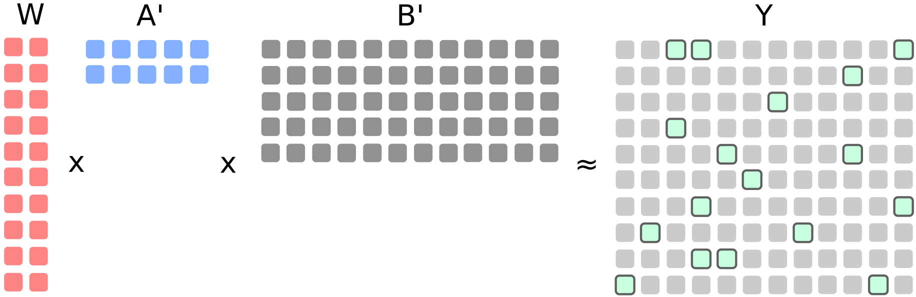


$$\underset{W,A}{\arg\min} \|P_\Omega(WA'B' - Y)\|_F^2 + \lambda \cdot \mathrm{rank}(A)$$

Solution 3: Matrix completion

Stanford University

Sparse longitudinal completion



$$\underset{W,A}{\arg\min} \|P_\Omega(WA'B' - Y)\|_F^2 + \lambda\|A\|_*$$

Sparse functional PCA fit

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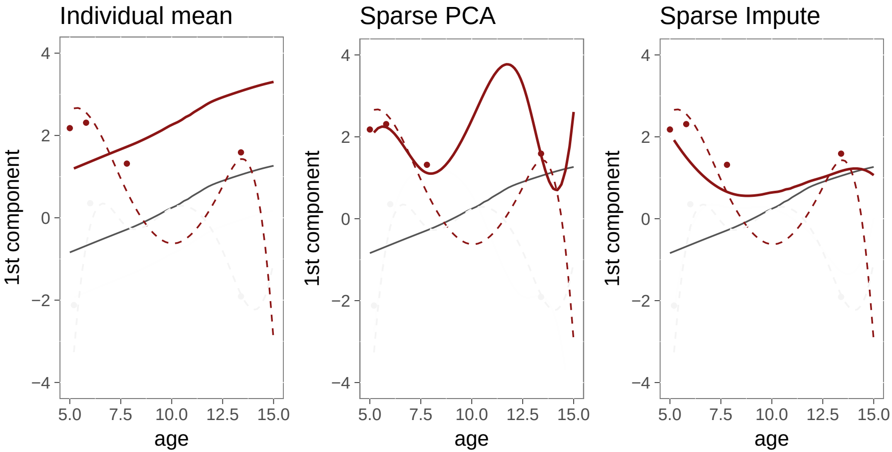
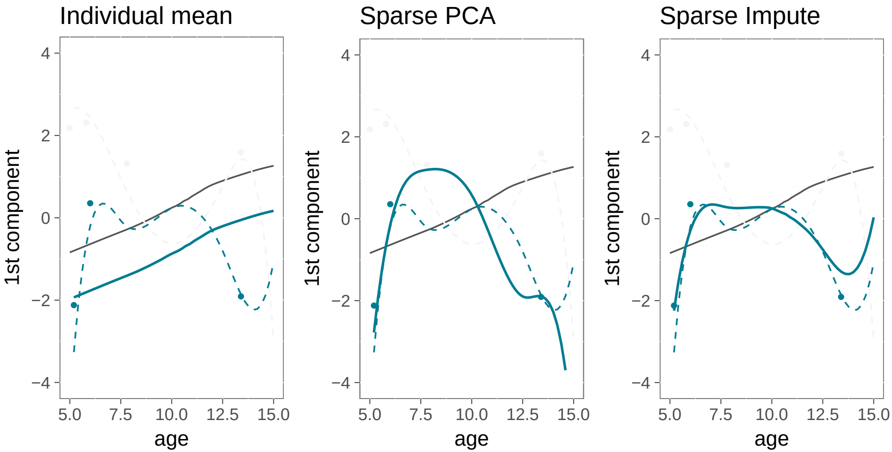


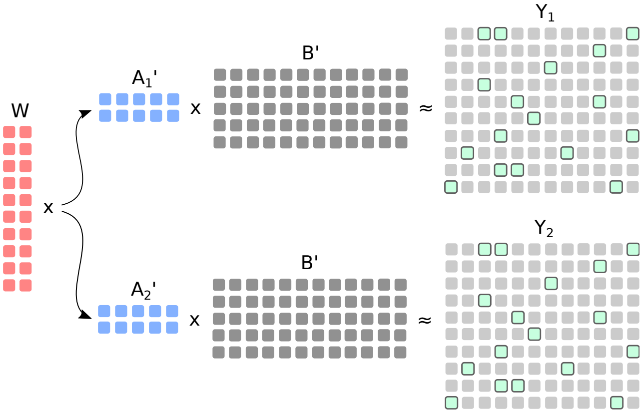
Sparse functional PCA fit



Solution 3: Matrix completion

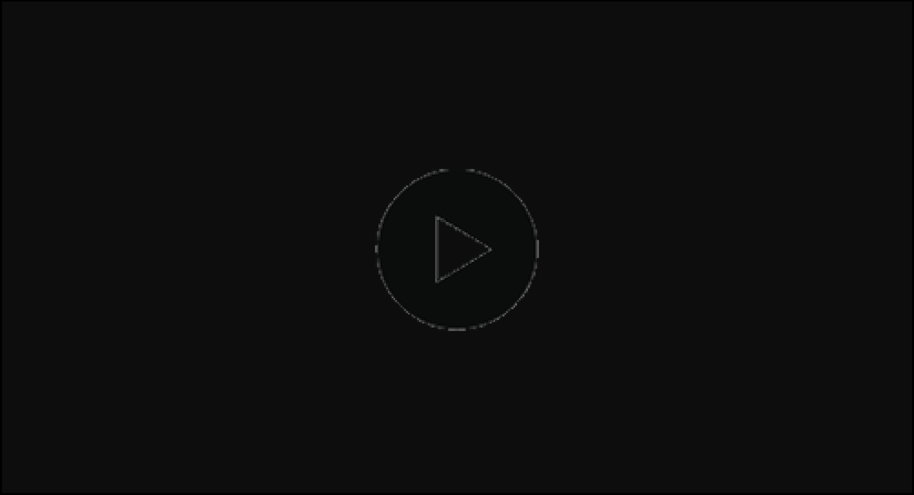
Stanford University

Multivariate sparse longitudinal completion

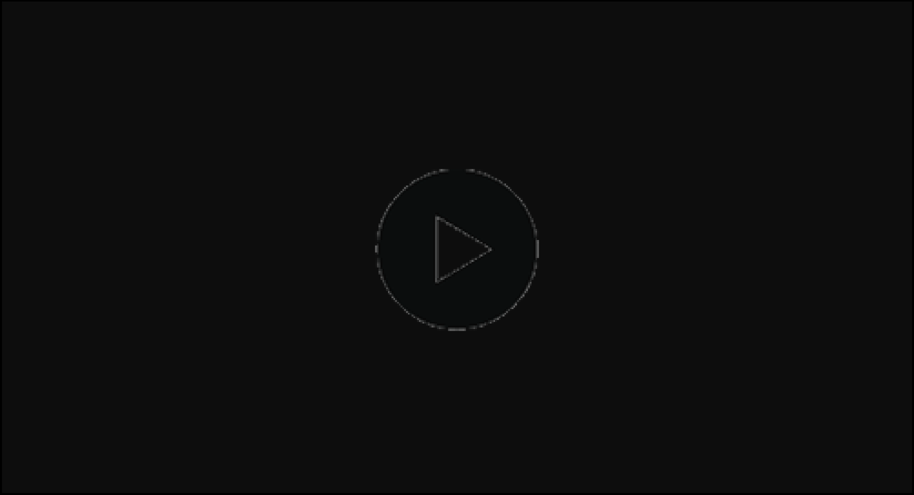


$$\underset{W,A}{\arg\min} \|P_{[\Omega,\Omega]}(W[A_1', A_2']B' \otimes I_2 - [Y_1, Y_2])\|_F^2 + \|[A_1', A_2']\|_*$$

PCA plane in OpenSim

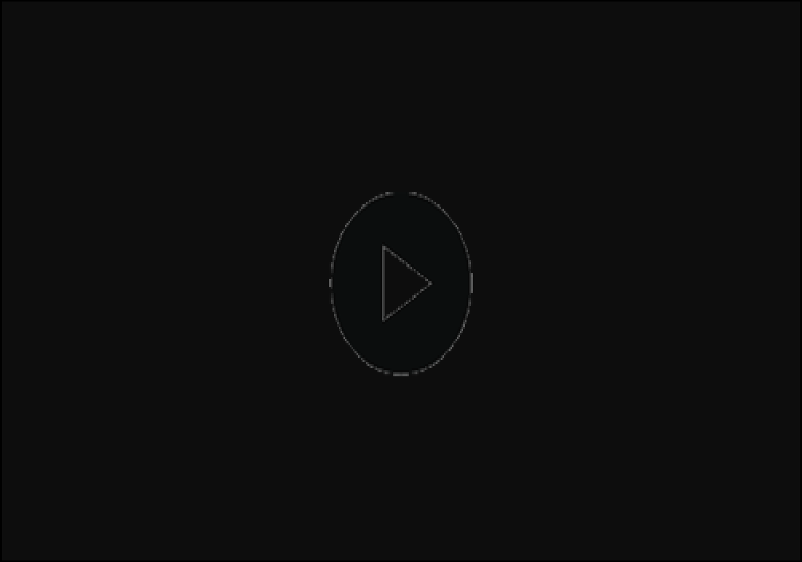


PCA plane in OpenSim



Predicting surgical outcome

Cerebral palsy



Problem

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Data:

- Musculoskeletal model

Problem:

- Synthesize movement
- Approximate brain function

Problem

Stanford University

Data:

- Musculoskeletal model

Problem:

- Synthesize movement
- Approximate brain function

Successes @ OpenAI

OpenSim in one slide

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$$S_{t+1} = M(S_t, a_t),$$

where

S_t - state at time $t \in \{1, ..., T\}$

a_t - vector of muscle excitations

M - OpenSim model

Walking

Stanford University

Go as far as you can minimizing the cost

$$\arg\max_{\{a_t:t\}} \sum_{t=1}^{T} v(S_t) - \tilde{c}(S_t)$$

$$\text{s.t. } \forall_t \; S_t = M(S_{t-1}, a_t)$$

One possible solution – policy gradient

Stanford University

Go as far as you can minimizing the cost

$$\arg\max_{\theta} \sum_{t=1}^{T} v(S_t) - \tilde{c}(S_t)$$

$$\text{s.t. } \forall_t \; S_t = M(S_{t-1}, P_\theta(S_{t-1}))$$

Installing OpenSim with python

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```
$ conda create -n opensim-rl -c kidzik osim-rl
$ source activate opensim-rl
$
$ python
> from osim.env import RunEnv
>
> env = RunEnv(visualize=True)
> for i in range(500):
>     observation = env.step(env.action_space.sample())
```

Standing

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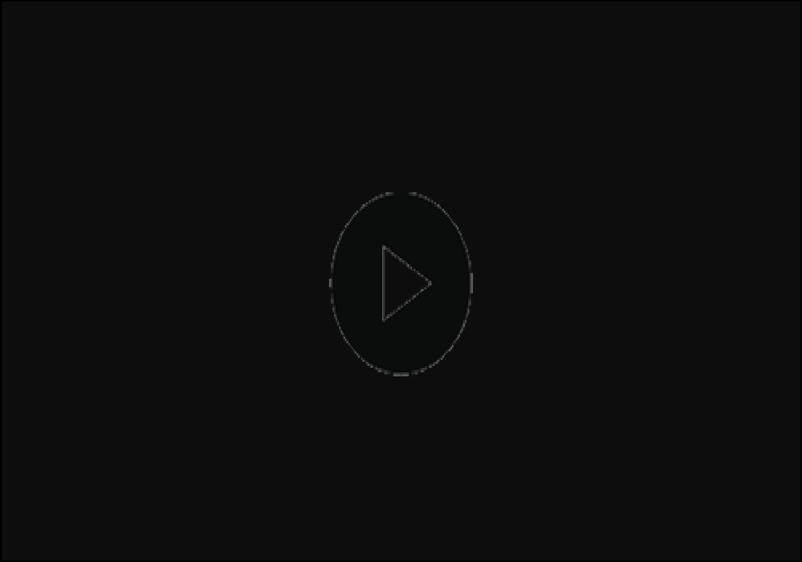
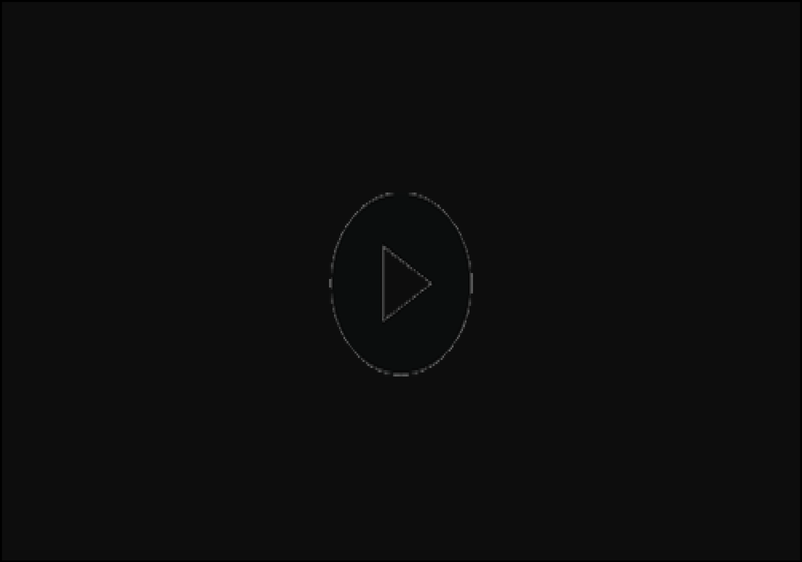


Standing penalized



Setup

State:

- Position/velocity of center of mass, toes, ankles, pelvis and head
- Joints angles/velocities/accelerations

Action:

- Activation of 18 muscles

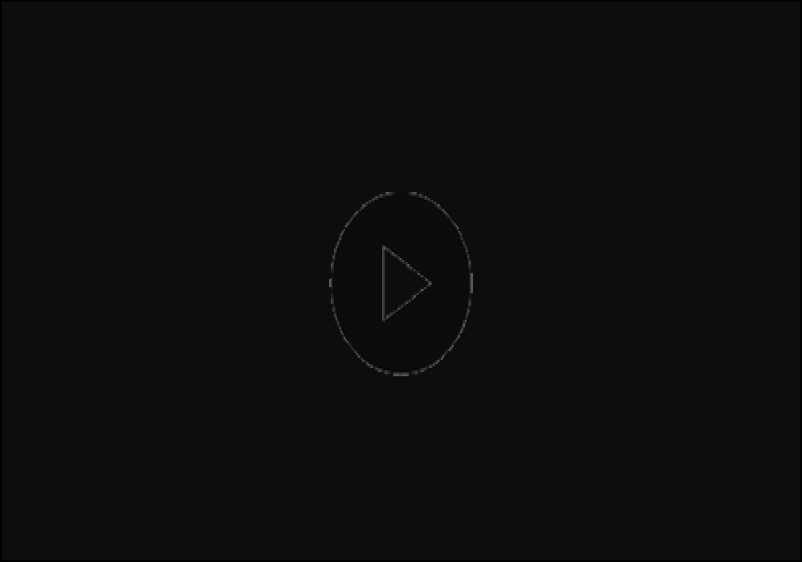
Reward:

- Net Δ of pelvis $-$ penalty on ligament forces

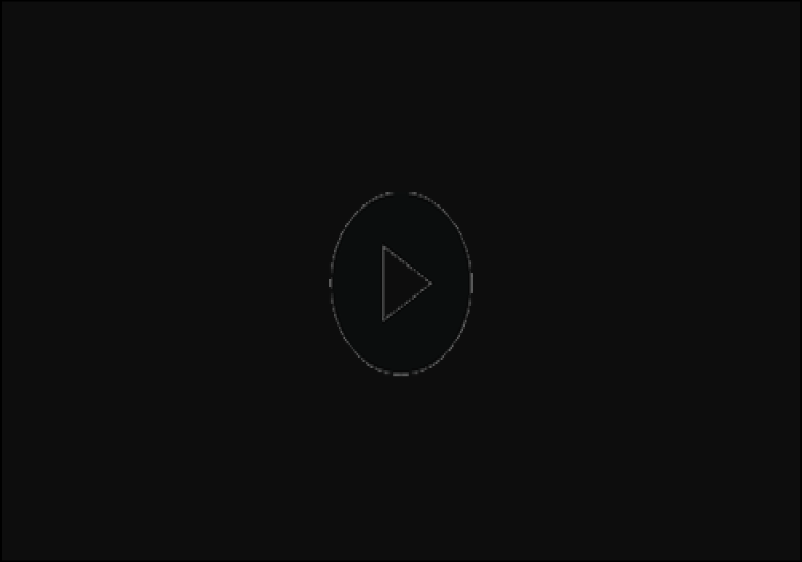
Signal @ $100Hz$

Walking 1 step

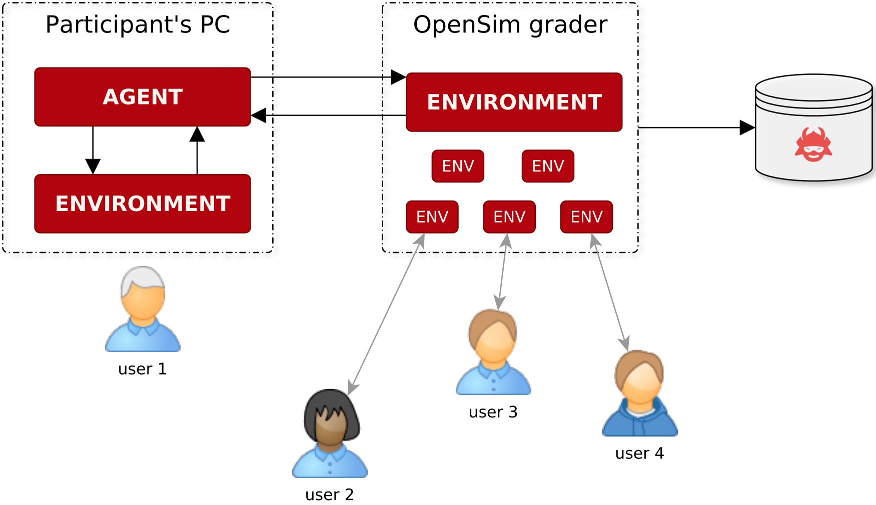
Stanford University



Walking 2 steps



The power of a **smart** crowd


Participant's PC
AGENT
ENVIRONMENT
OpenSim grader
ENVIRONMENT
ENV
ENV
ENV
ENV
ENV
user 1
user 2
user 3
user 4

NIPS 2017: Learning to Run

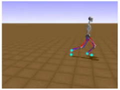
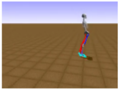
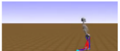
Reinforcement learning environments with musculoskeletal models

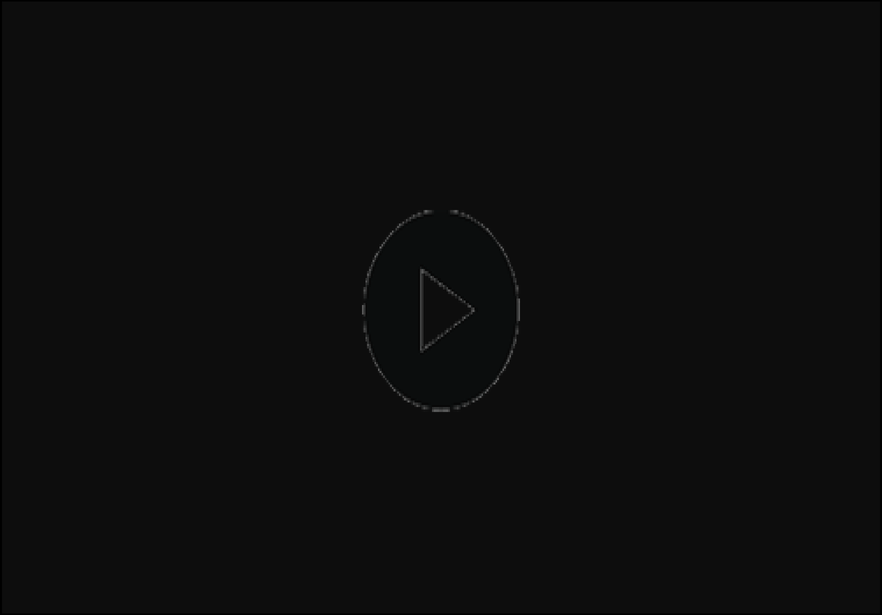
By Stanford Neuromuscular Biomechanics Laboratory

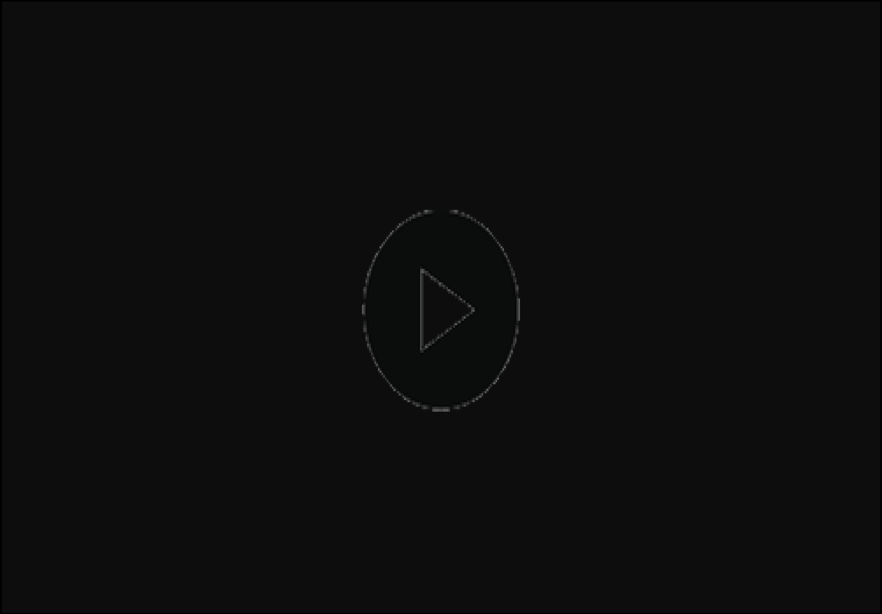
25 Days left | 45444 Views | 428 Participants | 1596 Submissions

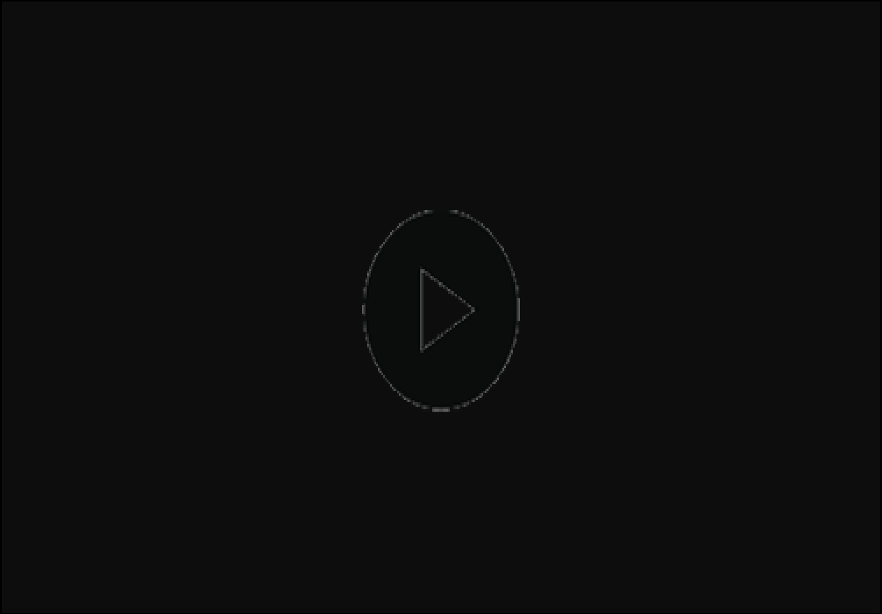
191 FOLLOW

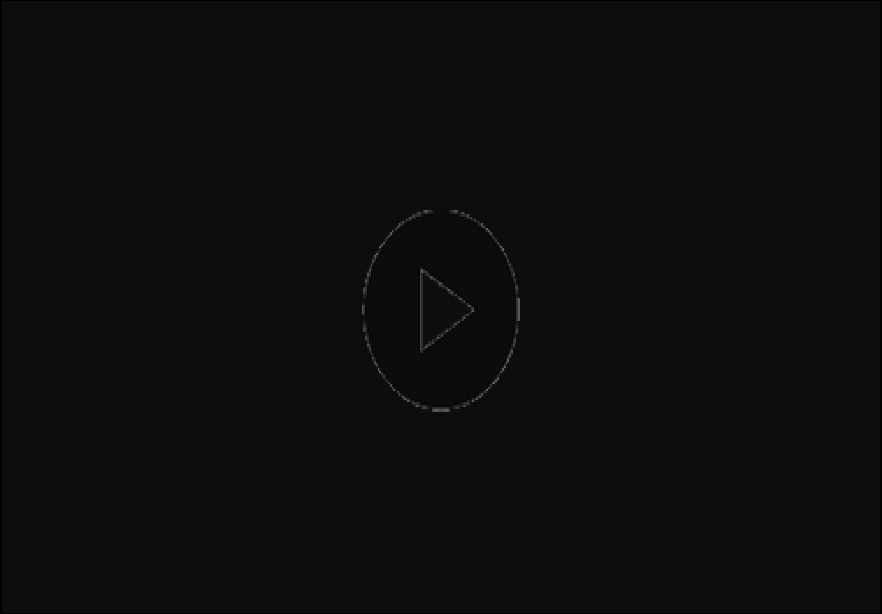
Overview Leaderboard Discussion Dataset

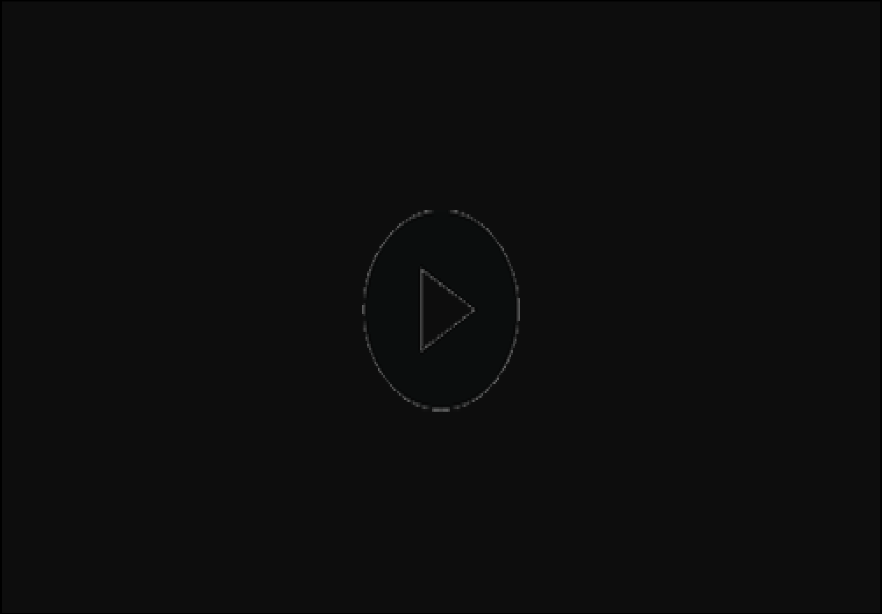
#	Participant	Video	Mean Reward per Simulation	Entries	Last Submission (UTC)
01.	JGeek		42.214518	56	Tue, 3 Oct 2017 19:08
02.	Henryk		41.61743	9	Sat, 23 Sep 2017 19:41
03.	Anton Pechenko		38.549363	87	Sat, 23 Sep 2017 11:44

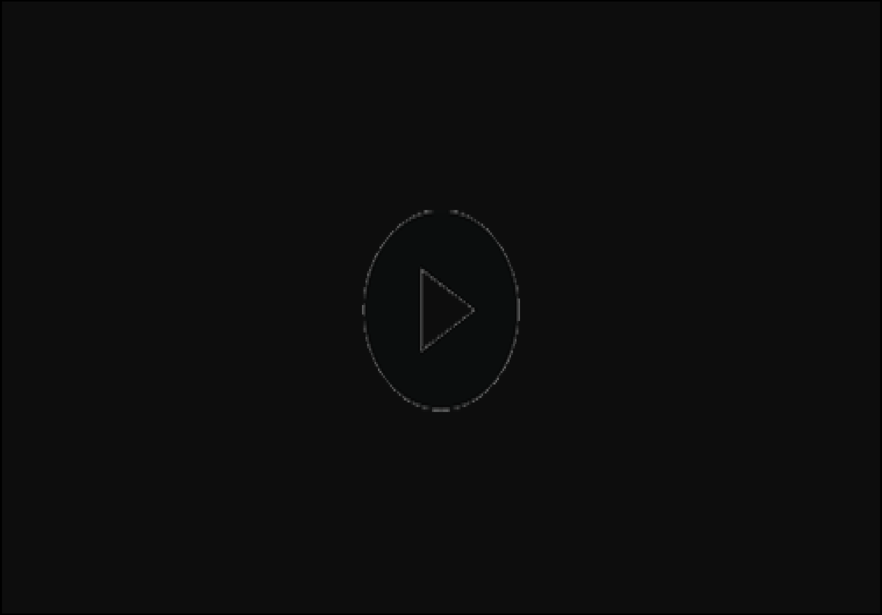


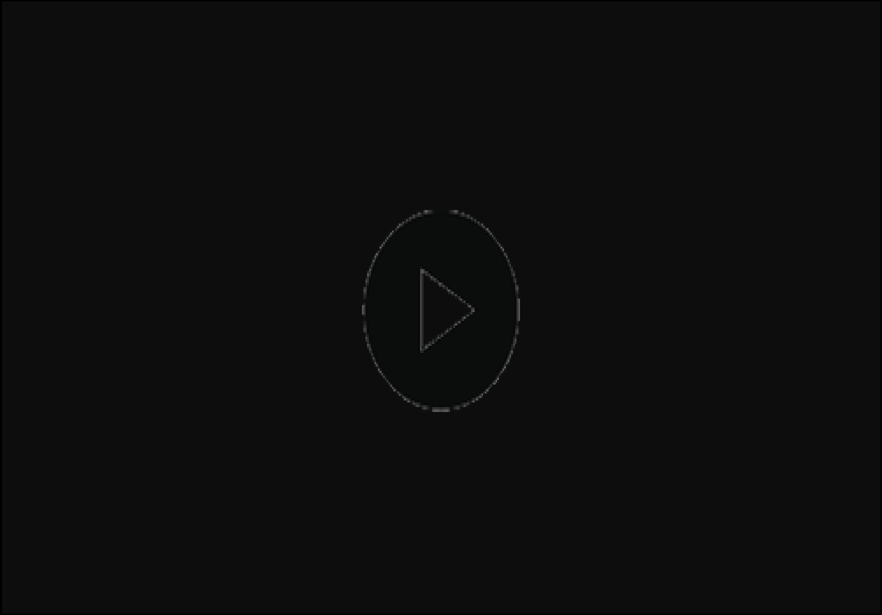


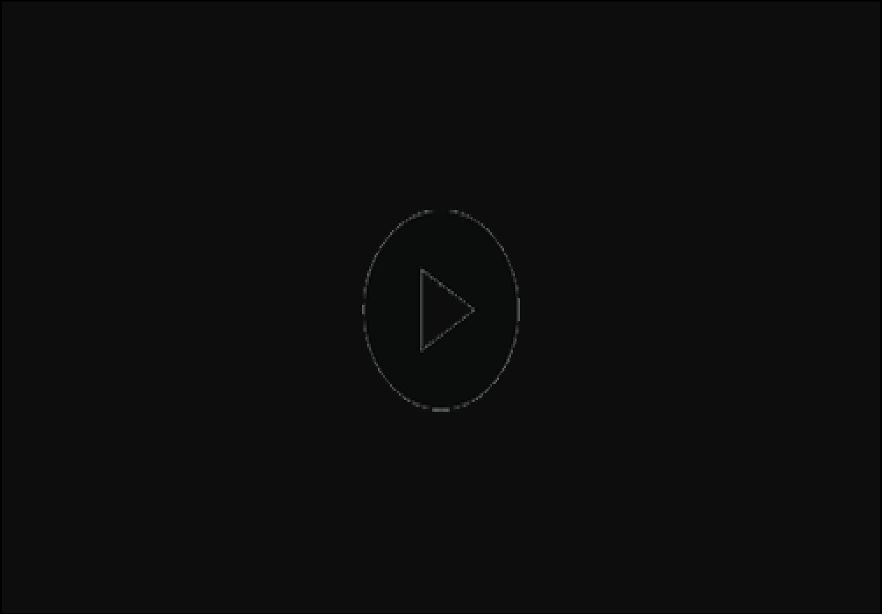


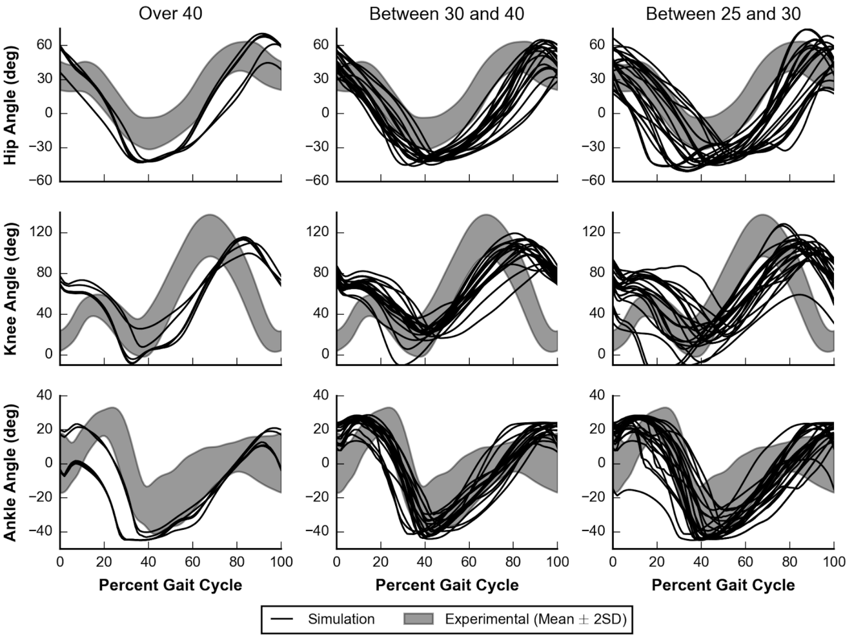


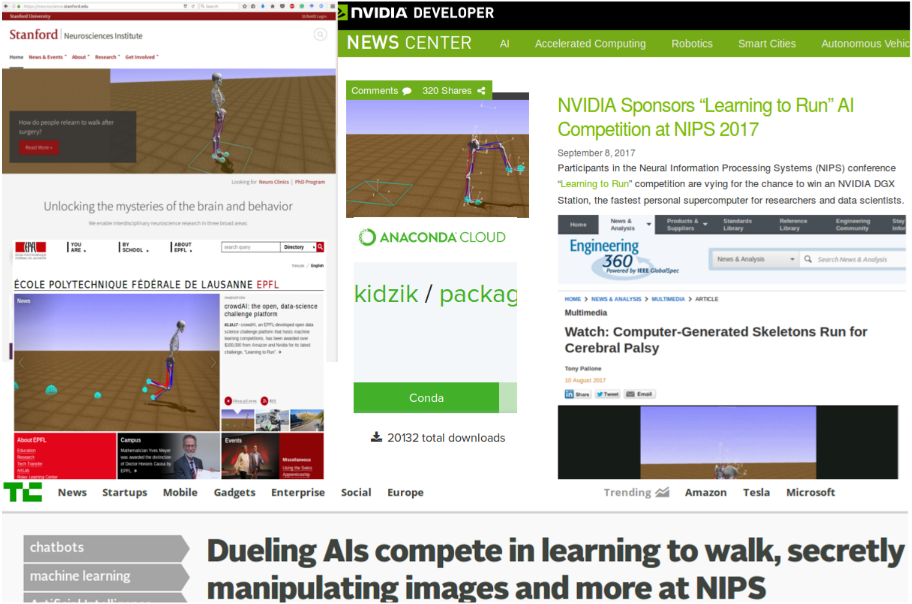









Over 40
Between 30 and 40
Between 25 and 30
Hip Angle (deg)
Knee Angle (deg)
Ankle Angle (deg)
60
30
0
−30
−60
120
80
40
0
40
20
0
−20
−40
0
20
40
60
80
100
Percent Gait Cycle
Simulation
Experimental (Mean ± 2SD)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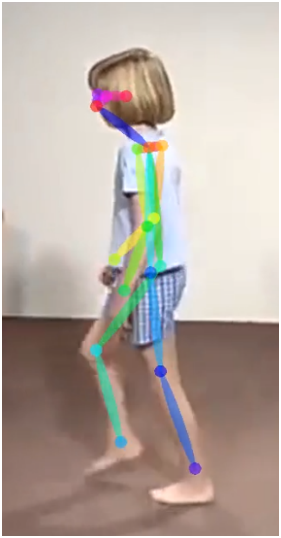
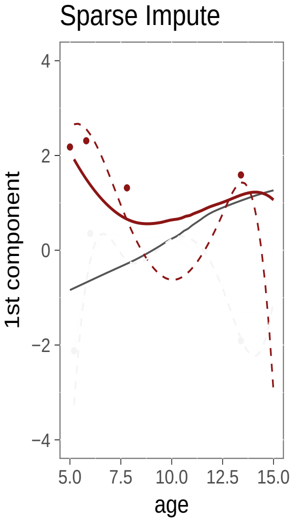
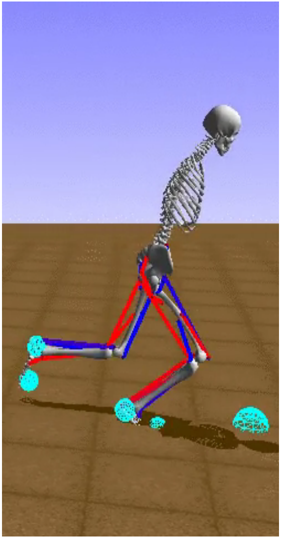
Dense but noisy



Rich but sparse



Expert but biased



One possible solution – policy gradient

- Let $P_\theta(s)$ be a parametric model of the policy
- Let $Q(s, a)$ be approximation of a state-action value
- Optimize $J(\theta) = Q(s, P_\theta(s))$