Modeling Heart Rate and Activity Data for Personalized Fitness Recommendation

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Based on paper by Jianmo Ni, Larry Muhlstein, and Julian McAuley

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ML in Fitness

Challenging data

Available information:

- user data: age, weight, gender
- activity data: type, date, duration, time series: location, altitude, speed, heart rate
- other: sleep patterns, stress levels etc

Challenges:

- heterogeneous
- noisy, missing values
- health conditions changes over time
- high variance between users: large datasets, but data associated with each user is limited

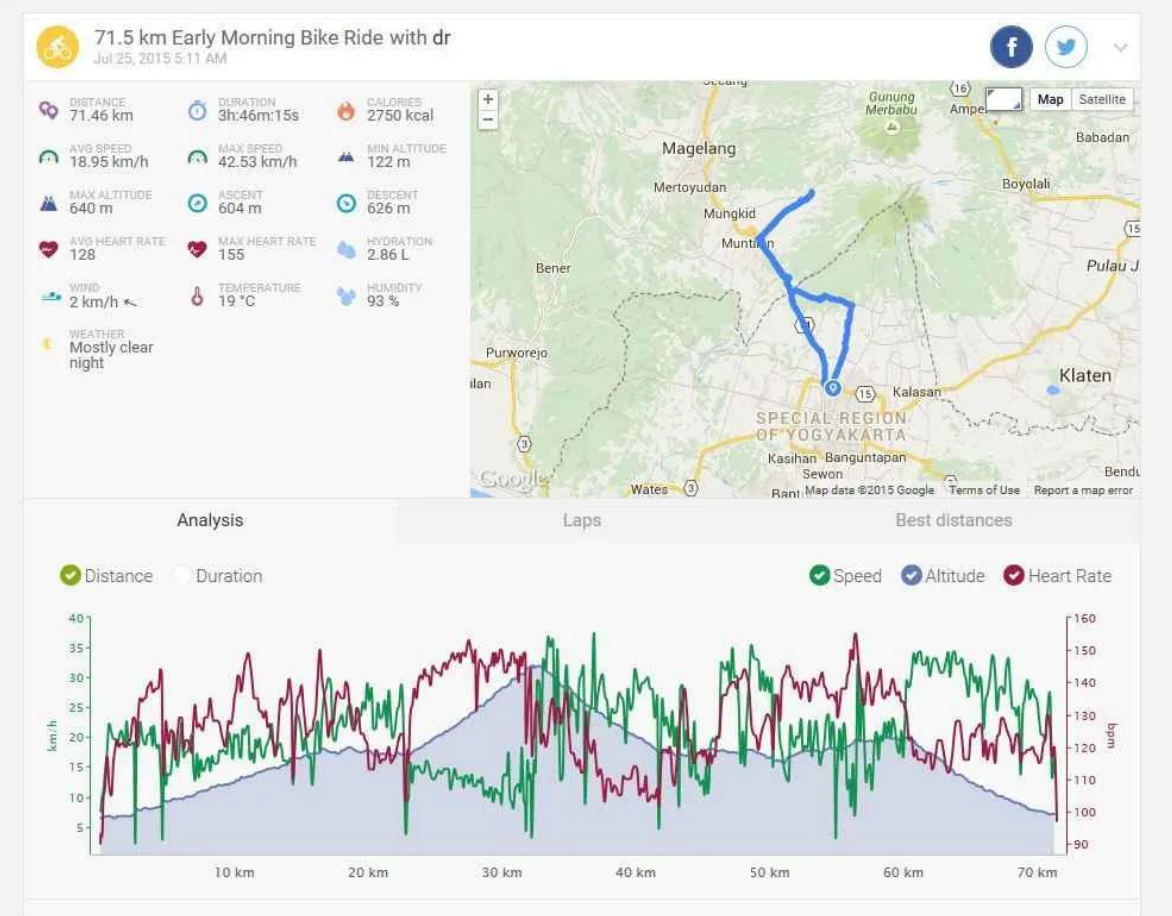
Examples of tasks

- Quantitative: predicting how some measurements will change during workout
- Qualitative: identifying features affecting workouts, clustering
- Recommendation: proposing route matching some fitness goals of user

In the paper: workout profile forecasting, short term prediction, recommendation tasks.

Endomondo Dataset

Endomondo



71.5 km Early Morning Bike Ride with dr
Jul 25, 2015 5:11 AM
DISTANCE
71.46 km
DURATION
3h:46m:15s
CALORIES
2750 kcal
AVG SPEED
18.95 km/h
MAX SPEED
42.53 km/h
MIN ALTITUDE
122 m
MAX ALTITUDE
640 m
ASCENT
604 m
DESCENT
626 m
AVG HEART RATE
128
MAX HEART RATE
155
HYDRATION
2.86 L
WIND
2 km/h
TEMPERATURE
19 °C
HUMIDITY
93 %
WEATHER
Mostly clear night
Map
Satellite
Magelang
Mertoyudan
Mungkid
Bener
Purworejo
Boyolali
Babadan
Klaten
Kalasan
SPECIAL REGION OF YOGYAKARTA
Kasihan
Banguntapan
Sewon
Wates
Map data ©2015 Google
Terms of Use
Report a map error
Analysis
Laps
Best distances
Distance
Duration
Speed
Altitude
Heart Rate
km/h
bpm
10 km
20 km
30 km
40 km
50 km
60 km
70 km

Dataset

Table 2: Description of variables

	Variable	Seq.	Unit
Measure -ment	Heart Rate	✓	Beat per Minute (BPM)
	Timestamp	✓	Unix Timestamp
	Distance	✓	Mile
	Speed	✓	Mile per Hour (MPH)
Context -ual	UserID	✗	/
	Sport	✗	/
	Gender	✗	Male, Female
	Altitude	✓	Meter
	Longitude	✓	Degree
	Latitude	✓	Degree
Derived	Der. Distance	✓	Kilometer (KM)
	Der. Speed	✓	Kilometer per Hour (KMPH)

Table 3: Endomondo dataset statistics

Statistic	Original	Filtered	Re-sampled
# of workouts	253,020	167,373	102,343
# of users	1,104	956	887
Avg. length (hours)	5.998	1.486	1.059
Avg. span (days)	/	766	733

Processing:

- **derived data**
- **filtering**:
  - removing outliers
  - truncating sequences to 450 data points
  - discarding data with sampling interval > 1 min
  - dropping users with < 10 workouts (average: 175)
- **re-sampling**:
  - interpolating and re-sampling with 10 second interval

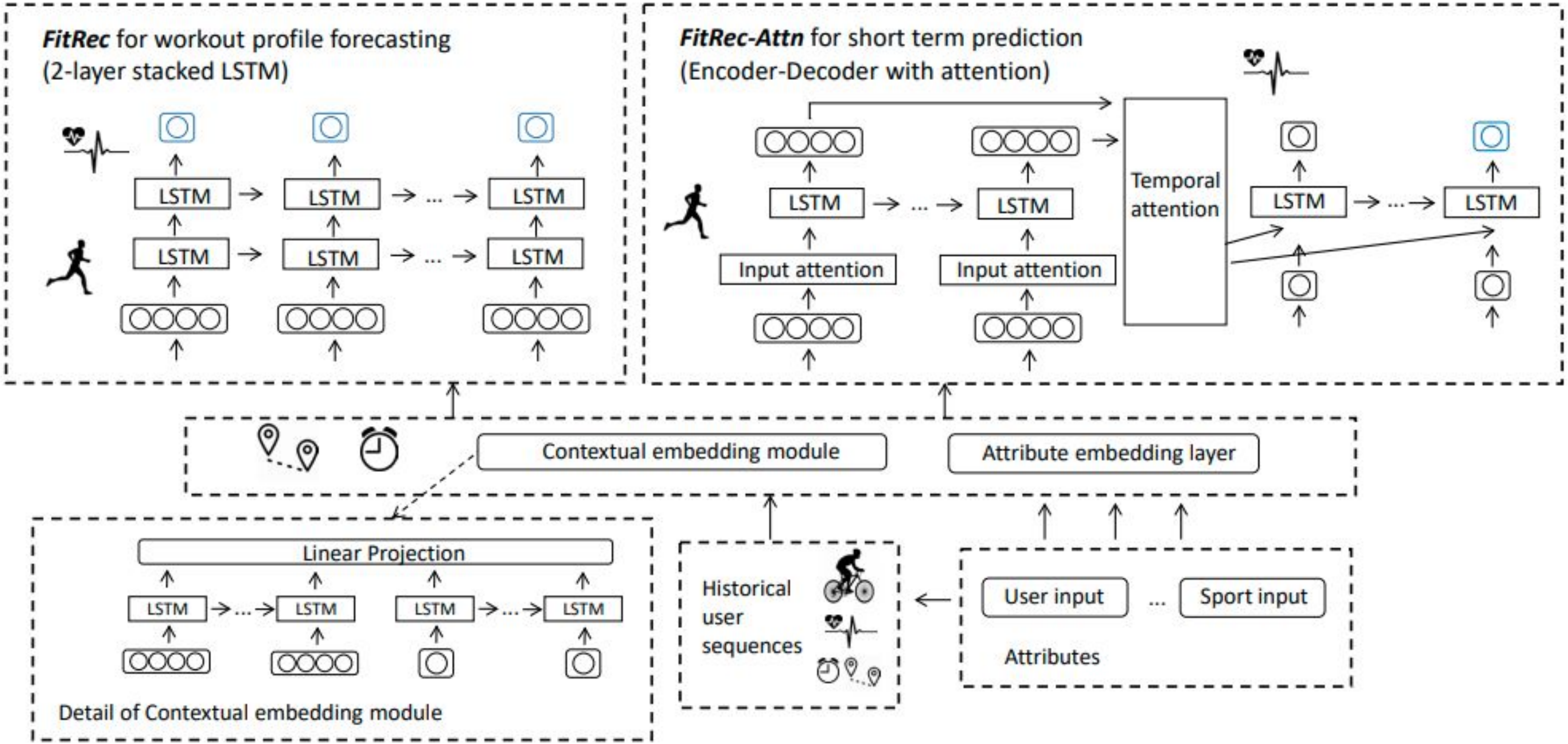
FitRec

Notation

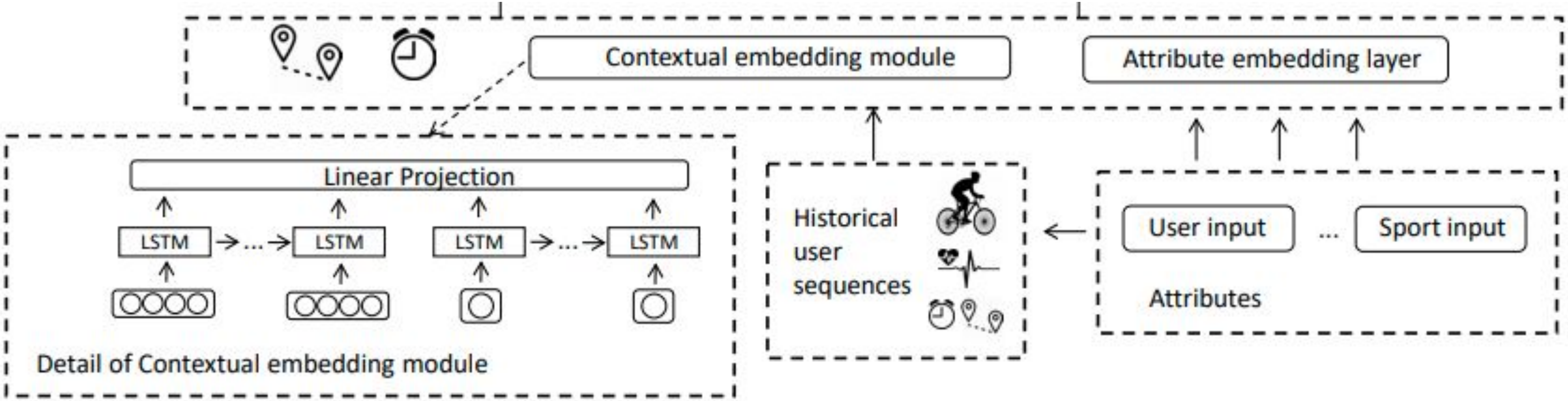
Notation	Description
$\mathcal{T}_{train}, \mathcal{T}_{test}$	training set and test set for two prediction tasks
$\mathbf{X}, \mathbf{Z} \in \mathbb{R}^{N \times T}$	contextual sequences of the current and the most recent workout
$\mathbf{y}, \mathbf{y}' \in \mathbb{R}^{T}$	target sequence of the current and the most recent workout
$\mathbf{a}$	attributes associated with the workout
T	length of input and target sequences
L	the number of sampled data points L
N	number of contextual sequences and each sequence is associated with a variable.
m	number of attributes
$\lvert a_i \rvert$	number of distinct values of the ith attribute
D_1	dimension of attribute embeddings
D_2	dimension of contextual embeddings
$\mathrm{E}_{a_i} \in \mathbb{R}^{\lvert a_i \rvert \times D_1}$	embedding matrix of the ith attribute
$\mathbf{e}_{a_i} \in \mathbb{R}^{D_1}$	attribute embedding learned from the ith attribute
$\mathbf{e}_t \in \mathbb{R}^{D_2}$	contextual embedding learned from historical workout sequences

- **contextual sequences**: e. g. altitude, distance
- **target sequence**: e. g. heart rate/speed
- **attributes:** e. g. user ID, age, workout type

Architecture overview



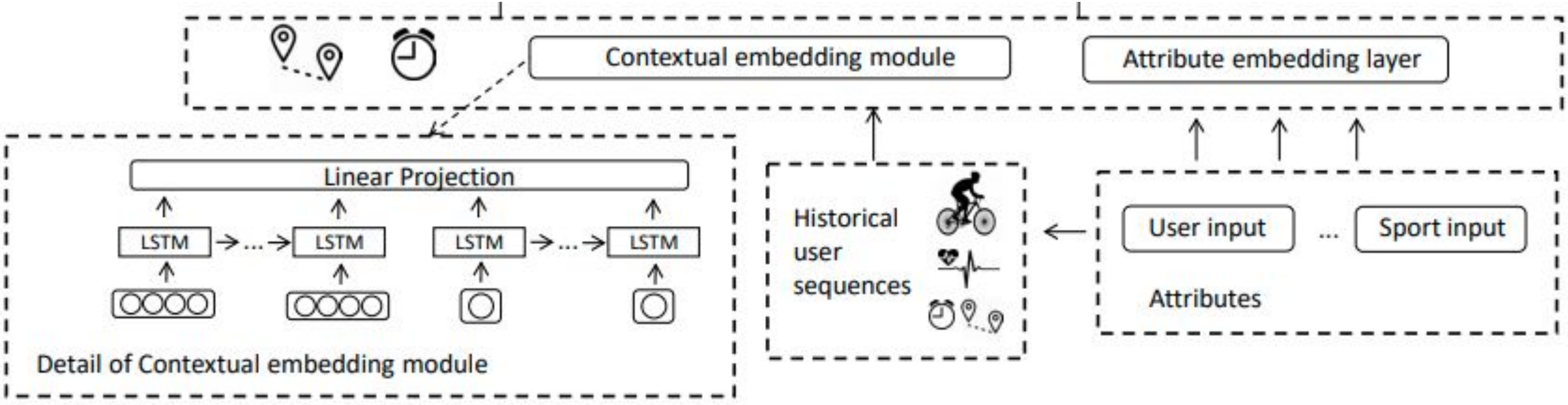
Common part: attribute embedding



Each type of attribute (sport type, gender etc) is one-hot encoded and has corresponding embedding layer, which transforms it into vector of size D_1 :

$$\mathbf{e}_{a_i} = \mathrm{E}_{a_i}(a_i), \forall i \in [1, m]$$

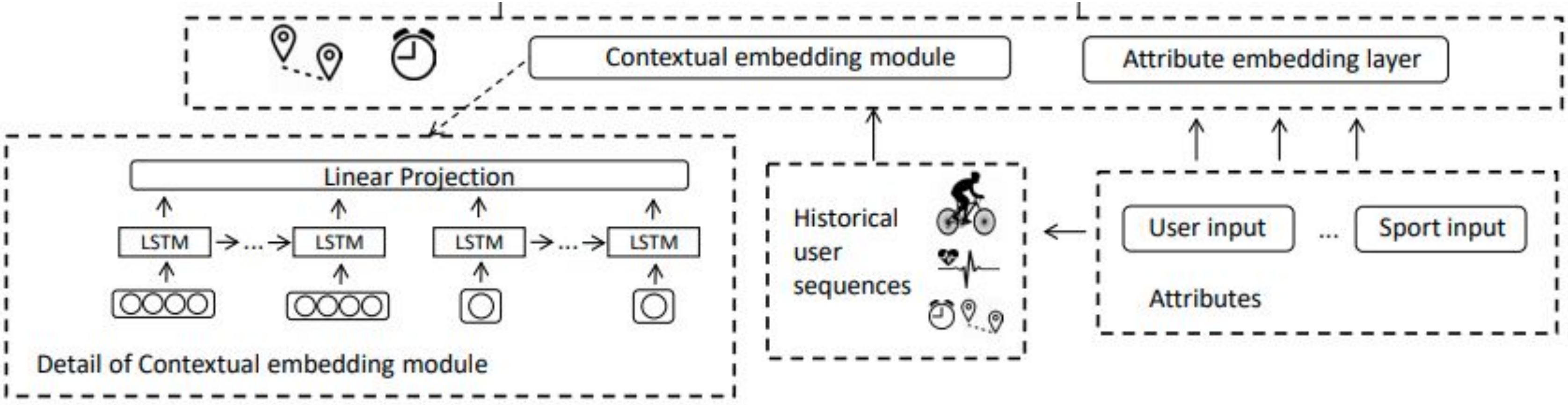
Common part: contextual embedding



Historical workout input sequences and target sequence are processed by separate LSTMs, which hidden states are concatenated and linearly projected:

$$\mathbf{h}_{1,t} = \mathrm{LSTM}_1(\mathbf{z}_t, \mathbf{h}_{1,t-1}),$$
$$\mathbf{h}_{2,t} = \mathrm{LSTM}_2(y'_t, \mathbf{h}_{2,t-1}),$$
$$\mathbf{e}_t = \mathbf{W}_e[\mathbf{h}_{1,t}; \mathbf{h}_{2,t}] + \mathbf{b}_e,$$

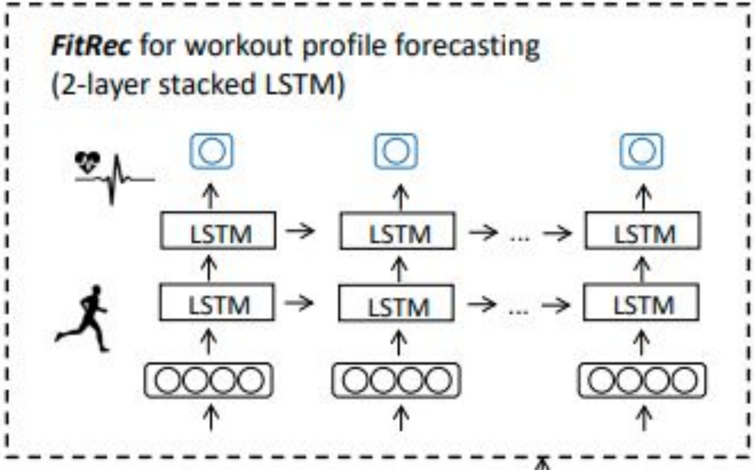
Common part: final embedding



Final embedding at each timestep is concatenation of input variables (of current workout), contextual embedding and attributes' embeddings:

$$\mathbf{u}_t = [\mathbf{x}_t; \mathbf{e}_t; \mathbf{e}_{a_1}; \ldots; \mathbf{e}_{a_m}],$$

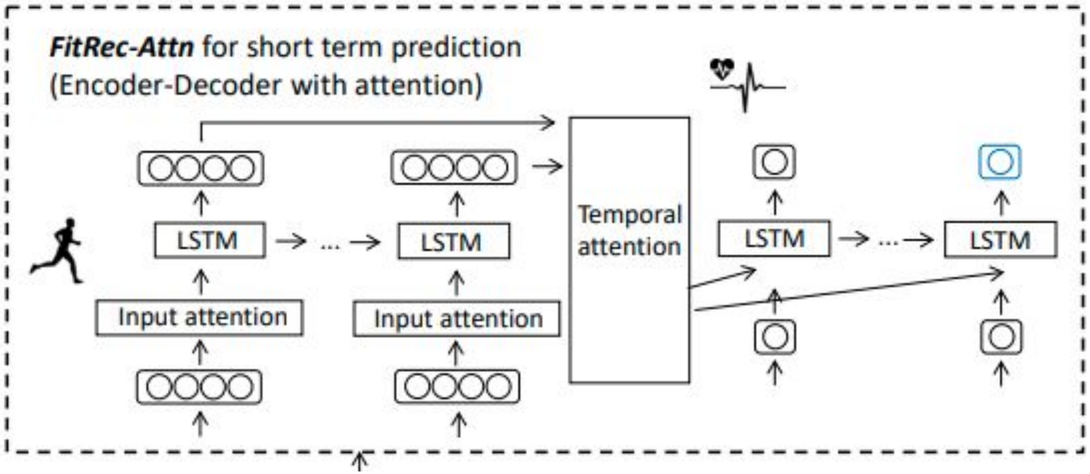
FitRec for workout profile forecasting



Embeddings are processed by 2 stacked LSTMs. Output is the linearly transformed hidden state of the 2nd one, passed through SELU:

$$\mathbf{h}_t = \mathrm{LSTM}(\mathbf{u}_t, \mathbf{h}_{t-1}),$$
$$\hat{y_t} = \mathrm{SELU}(\mathbf{W}_{NAT}\mathbf{h}_t + \mathbf{b}_{NAT}).$$

FitRec-Attn for short term prediction: input attention



Contextual embeddings from common part of network are first passed through attention layer and LSTM encoder:

$$\mathbf{u}^k = (u_1^k, \ldots, u_T^k)$$

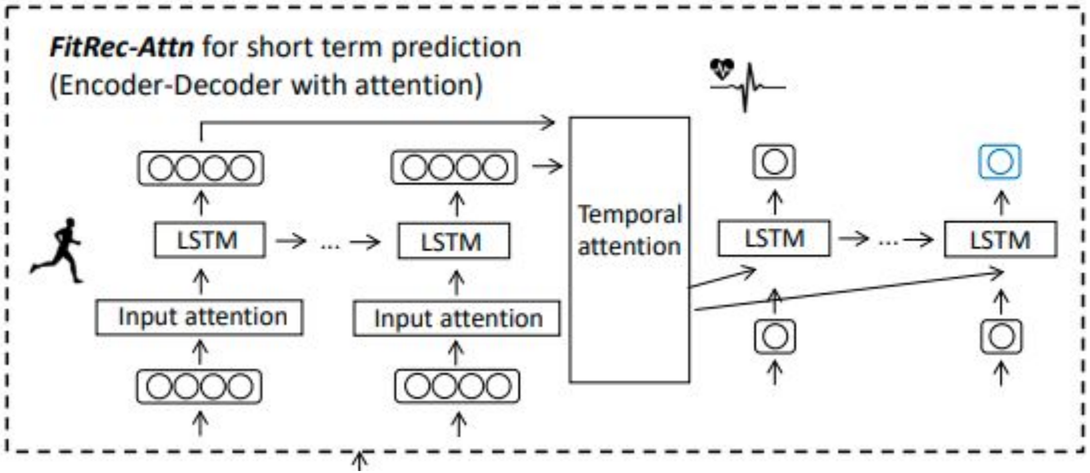
$$s_t^k = \mathbf{v}_s^\top (\mathbf{W}_s[\mathbf{h}_{t-1}; \mathbf{u}^k] + \mathbf{b}_s)\ 1 \le k \le K,$$

$$\alpha_t^k = \frac{\exp(s_t^k)}{\sum_{j=1}^K \exp(s_t^j)},$$

$$\tilde{\mathbf{u}}_t = (\alpha_t^1 u_t^1, \ldots, \alpha_t^K u_t^K)$$

$$\mathbf{h}_t = \mathrm{LSTM}_e(\mathbf{h}_{t-1}, \tilde{\mathbf{u}}_t)$$

FitRec-Attn for short term prediction: temporal attention



Encoder is followed with decoder, where attention over decoder and each encoder hidden states is calculated and processed by LSTM. Final prediction is calculated as linear transformation of last decoder hidden state and context vector.

$$l_t^i = \mathbf{v}_l^\top (\mathbf{W}_l[\mathbf{d}_{t-1}; \mathbf{h}_i] + \mathbf{b}_l) \; 1 \le i \le T,$$

$$\beta_t^i = \frac{\exp(l_t^i)}{\sum_{j=1}^T \exp(l_t^j)}, \quad \mathbf{c}_t = \sum_{i=1}^T \beta_t^i \mathbf{h}^i$$

$$\tilde{y}_{t-1} = \tilde{\mathbf{w}}^\top [y_{t-1}; \mathbf{c}_{t-1}] + \tilde{b},$$

$$\mathbf{d}_t = \mathrm{LSTM}_d(\mathbf{d}_{t-1}, \tilde{y}_{t-1}),$$

$$\hat{y_T} = \mathbf{W}_{AT}[\mathbf{d}_T; \mathbf{c}_T] + \mathbf{b}_{AT}$$

Training & evaluation

Objective function:

$$\mathcal{L} = \frac{1}{|N_{train}|} \sum_{\mathbf{y} \in \mathcal{T}_{train}} \sum_{t=1}^{L} (\hat{y_t} - y_t)^2$$

Evaluation metrics:

$$\text{RMSE} = \sqrt{\frac{1}{|N_{test}|} \sum_{\mathbf{y} \in \mathcal{T}_{test}} \sum_{t=1}^{L} (y_t - \hat{y_t})^2}$$

$$\text{MAE} = \frac{1}{|N_{test}|} \sum_{\mathbf{y} \in \mathcal{T}_{test}} \sum_{t=1}^{L} |y_t - \hat{y_t}|,$$

Training & evaluation procedure: data split by date, small network, gridsearch of hyperparameters, 50 epochs of training

Results: workout profile forecasting

Model	Speed (KMPH) RMSE	Speed (KMPH) MAE	Heart rate (BPM) RMSE	Heart rate (BPM) MAE
Global mean (train)	11.997	8.532	24.302	18.185
User mean (train)	10.690	6.418	20.117	15.090
MLP	8.998	4.411	18.256	13.918
FitRec (U)	7.144	2.472	18.784	14.142
FitRec (U/S)	7.073	**2.381**	17.325	13.012
FitRec (U/S/G)	7.328	2.396	18.207	13.831
FitRec (U/S/C)	**7.025***	2.384	**17.051***	**12.847***

- Input: expected workout time, specified route
- Baselines:
  - global/user mean
  - MLP (non-recurrent neural network working on concatenated attribute embeddings, contextual embeddings and contextual input)
- U - user, S - sport, G - gender, C - context = previous workout

Results: short term prediction

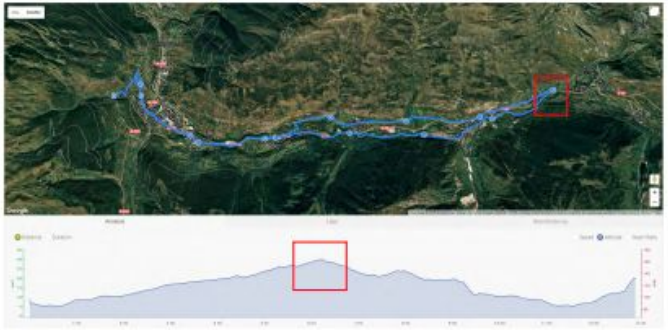
	Heart rate (BPM)	
Model	RMSE	MAE
Windowed MLP	3.035	1.919
Seq2Seq+A	2.807	1.720
DA-RNN	2.816	1.733
FitRec-Attn (U)	2.795	1.705
FitRec-Attn (U/C)	**2.783***	**1.695***

- Input: speed and altitude sequences, heart rate values in a few last timesteps
- Baselines:
  - windowed MLP - MLP using sliding window
  - Seq2Seq+A - encoder-decoder with temporal attention
  - DA-RNN - encoder-decoder with input and temporal attention
- Seq2Seq and DA-RNN model didn't use attribute and contextual embeddings

Personalized recommendation tasks

- **Workout route recommendation**: given expected workout criteria (e.g. time, heart rate or speed profile), suggest routes from historical data that match user's expectation
- **Short term heart rate prediction**: predict whether a user's heart rate will exceed some threshold if they continue the workout

(a) Map of the ground-truth route.



(b) Map of the recommended alternate route.

Route recommendation: approach

Producing recommendations (heart rate):

1. Given a set of routes to choose from, FitRec is used to predict heart rate profile for each of them
2. The produced heart rates profiles are compared with the target/preferred profile specified by user
3. Routes are sorted based on similarity score of their predicted profile to the target. Ranking of recommendations is produced.

Route recommendations: evaluation

1. For each workout in user's test set, consider it's route as positive sample and randomly select another 100 routes as negatives
2. Ask model for recommendation using the e.g. heart rate of the positive route as preference
3. Evaluate the ranking of routes (the positive and 100 negative ones) using commonly-used ranking-based metrics - we want positive route to be high in the ranking

Table 7: Route recommendation performance

	AUC	Hit@10	NDCG
User mean (train)	0.500	0.100	/
MLP	0.506	0.106	0.212
FitRec (U)	0.639	0.214	0.262
FitRec (U/S)	0.643	0.234	0.266
FitRec (U/S/C)	**0.673**	**0.272**	**0.284**

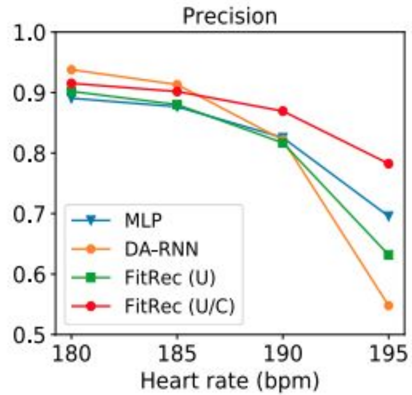
Short term excessive heart rate prediction

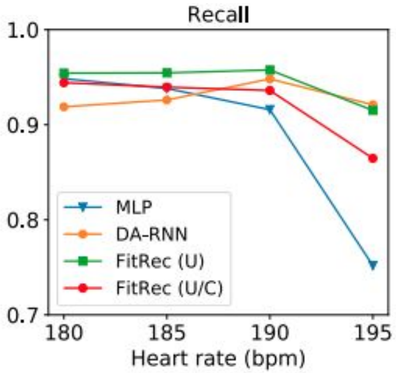
Approach:

1. FitRec-Attn is used to predict heart rate at each step; predicted value is compared with the threshold to see if it exceeds it

Evaluation:

1. 2 binary sequences are produced: the first one contains 1 where ground truth heart rate exceeded the threshold, the second uses predicted heart rate
2. Precision, recall and F1 score are calculated





Conclusions

Contributions:

- Endomondo dataset
- FitRec & FitRec-Attc - LSTM & attention-based systems for addressing sequential prediction problems in fitness, exceeding other models while solving some of quantitative and recommendation tasks

Thanks for your attention!

Resources

- paper: https://cseweb.ucsd.edu/~jmcauley/pdfs/www19.pdf
- dataset: https://sites.google.com/eng.ucsd.edu/fitrec-project/home
- code: https://github.com/nijianmo/fit-rec