

Communication Technologies 2 (CT2)

Machine Learning: Applications and Algorithms

Activity Recognition: Evaluation metrics

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- Activity Recognition
- Instance-based Activity Recognition
- Event-based Evaluation
- Summary

ACTIVITY RECOGNITION (AR)

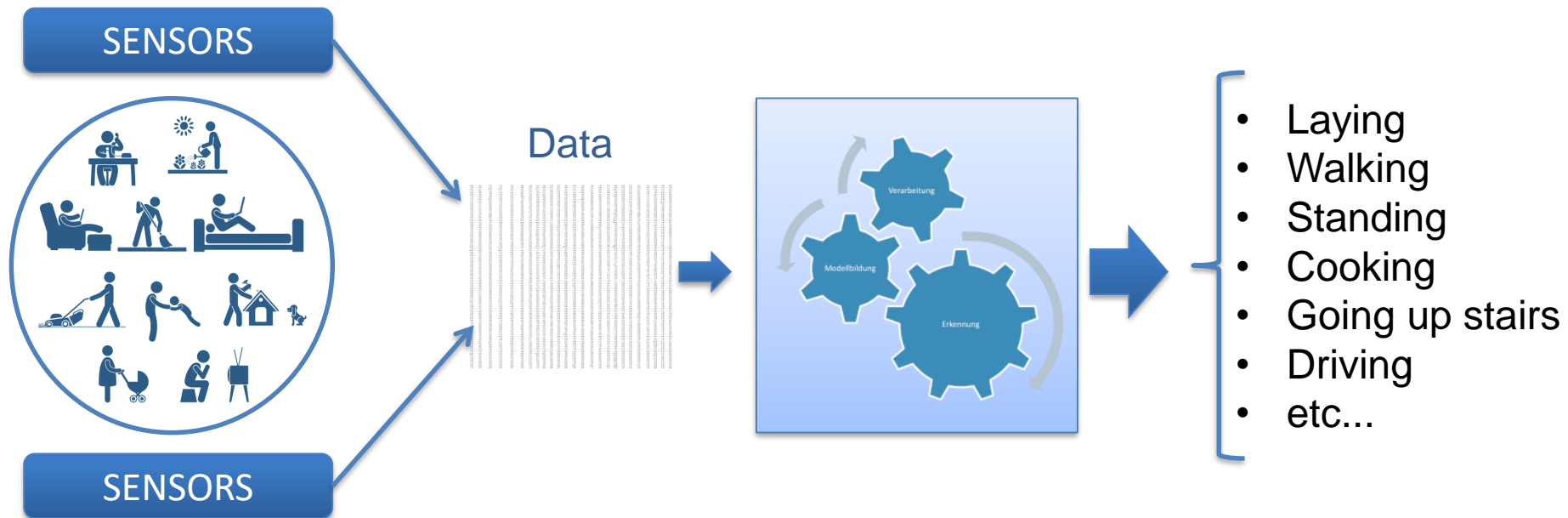
Activity Recognition (AR)

...to recognize the actions and intentions of a user based on a group of observations



Daily Life Activities

Activity Recognition (AR)



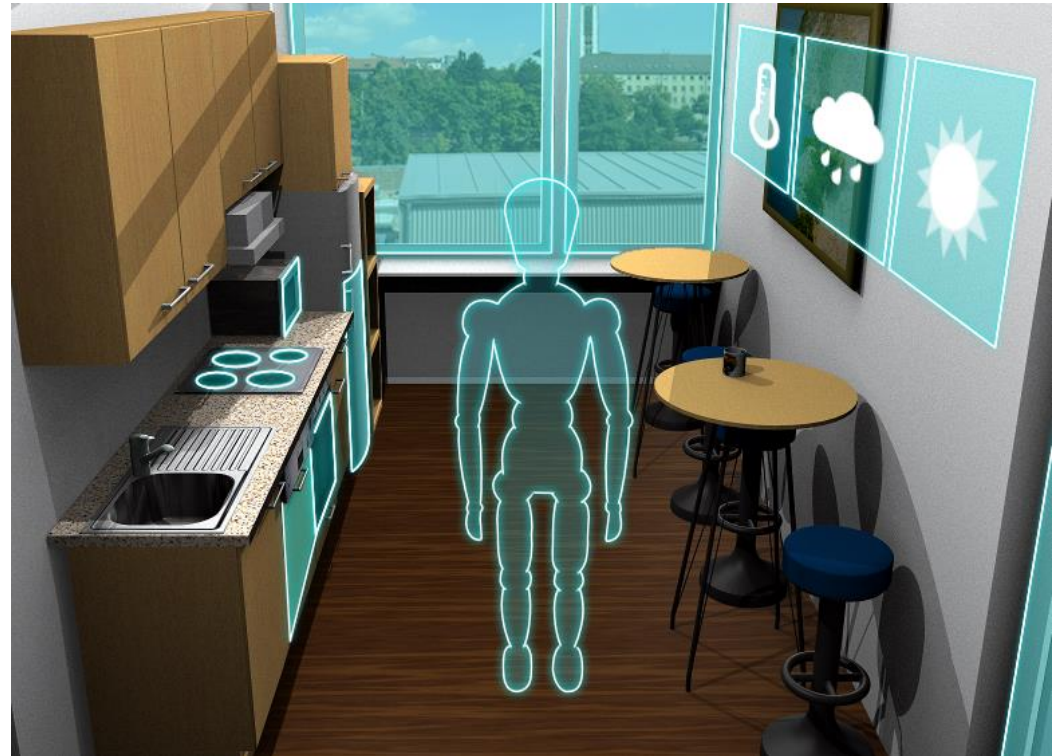
Activity Recognition (AR)



Sensor-based Activity Recognition

Dense Sensing

- Attached to objects to monitor human activities through user-object interactions
- Suitable for activities that involve a number of objects within an environment



[ComTec]

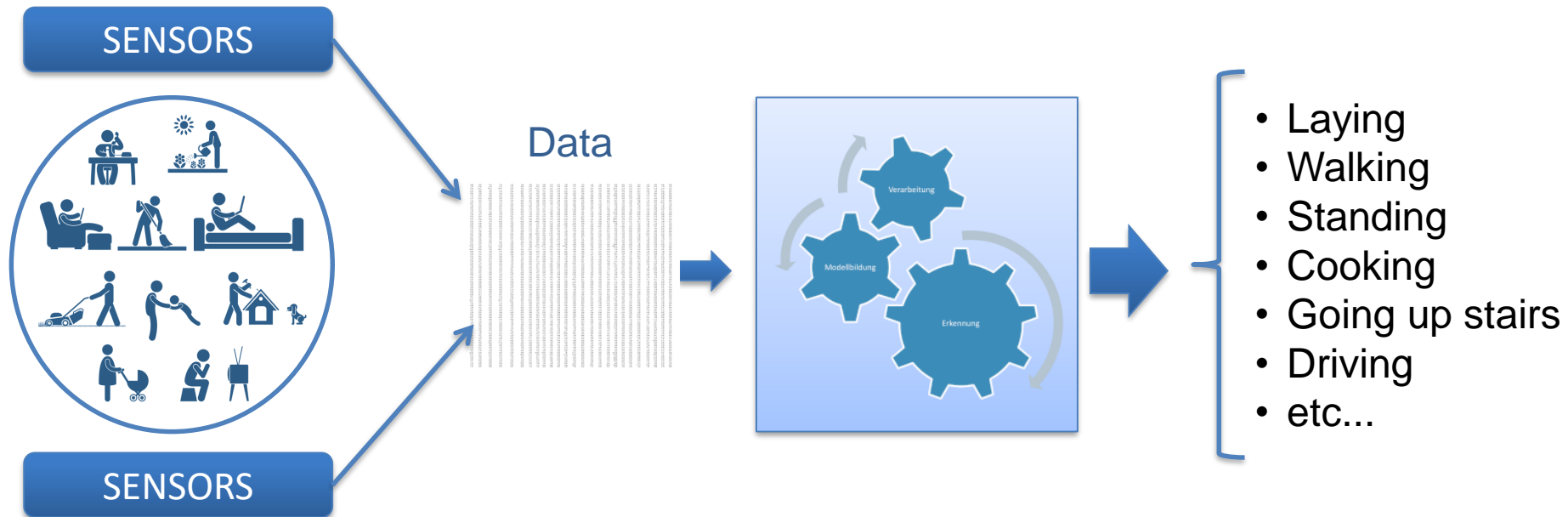
Wearable Sensing

- Can be positioned directly or indirectly on the body
- Sensors be embedded into, clothes, mobile devices, etc.
- Position, pulse, skin temperatures
- Mainly physical activities like walking, running, etc.

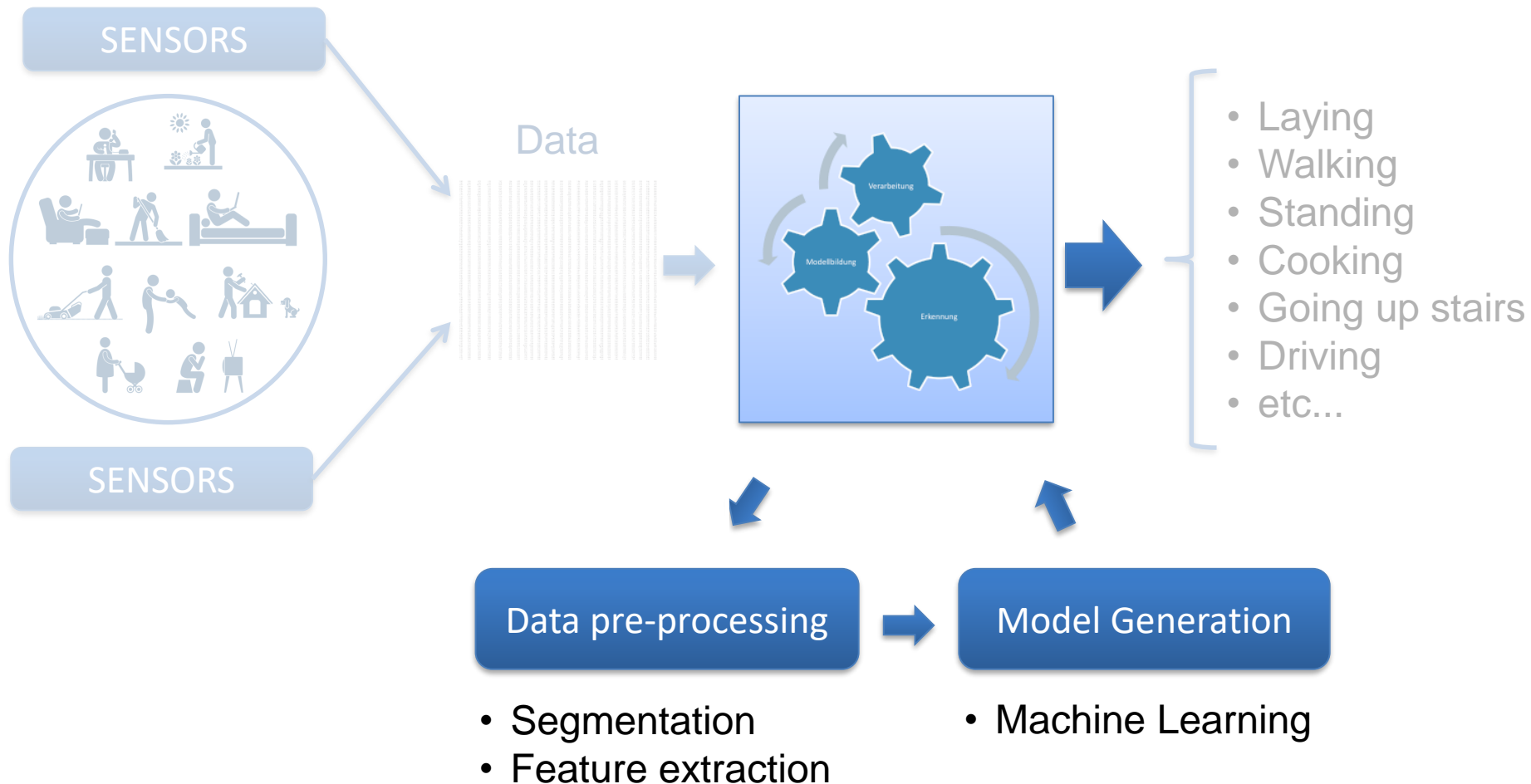


[1]

Activity Recognition Process



Activity Recognition Process



Machine learning



Supervised

- Bayesian statistics
- Decision trees
- Artificial neural network
- Support vector machines
- Hidden Markov models
- Etc...

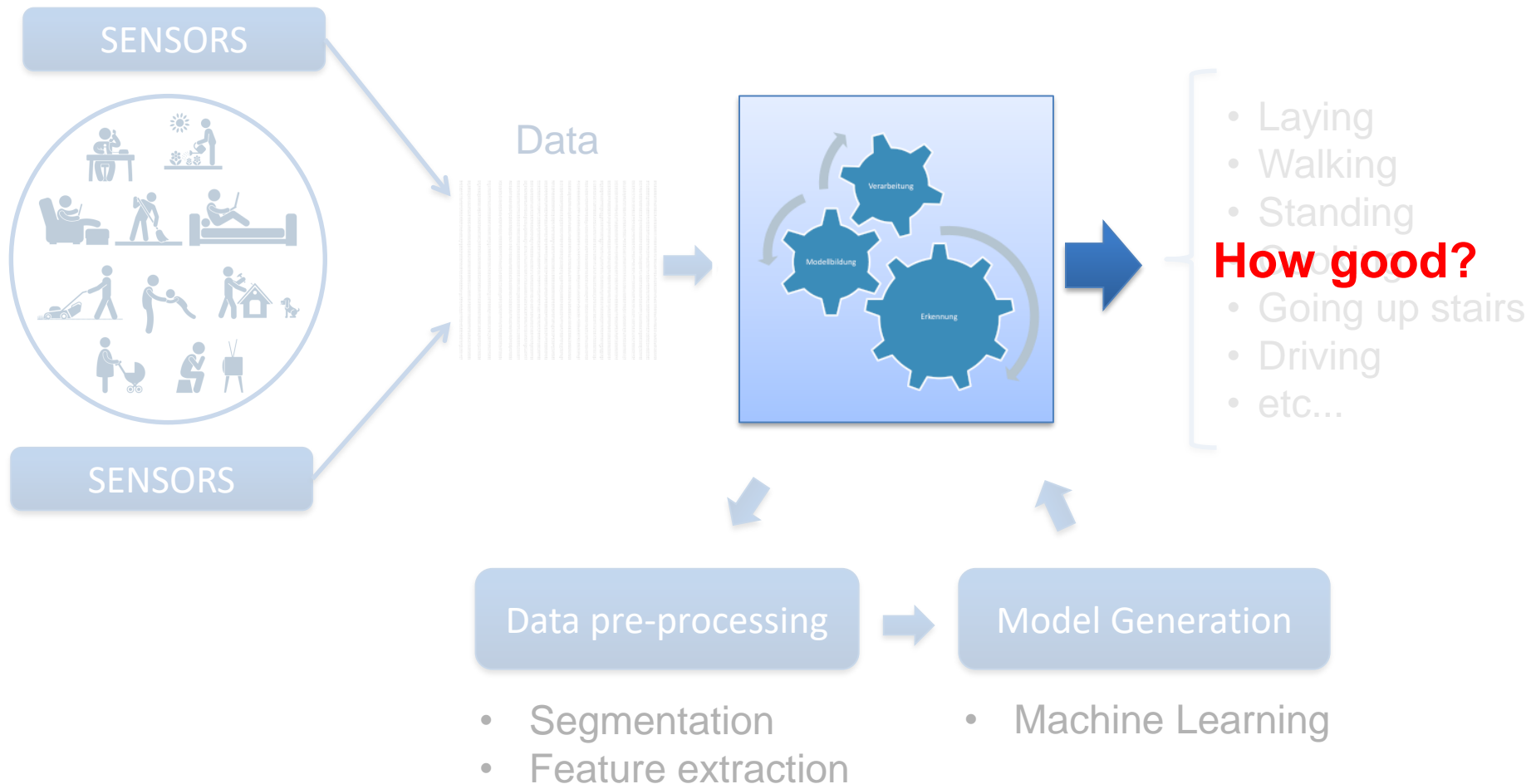
Unsupervised

- Data clustering
- Self-organizing map
- Artificial neural network
- Expectation-maximization algorithm
- Etc...

Reinforcement

- Monte Carlo Method
- Q-learning
- Temporal difference learning
- Learning Automata
- Etc...


Activity Recognition Process



INSTANCE-BASED ACTIVITY RECOGNITION

Instance-based AR

- An instance is a vector that contains all features calculated within a segment
- For supervised learning the instance is labeled with an activity



	Ground Truth	Recognized by the model
1	step down	step down
2	walking	step down
3	walking	walking
4	sitting	sitting
...

Example – 3 activities / 300 instances

Activity	Total count of Instances
step down	100
walking	100
sitting	100
Σ	300

Example – 3 activities / 300 instances

Activity	Total count of Instances
step down	100
walking	100
sitting	100
Σ	300

time
↓

Ground Truth	Recognized
step down	step down
walking	step down
walking	walking
sitting	sitting
...	...

Example – 3 activities / 300 instances

Activity	Total count of Instances	Correct recognized Instances
step down	100	100
walking	100	95
sitting	100	90
Σ	300	285

time ↓	Ground Truth	Recognized
	step down	step down
	walking	step down
	walking	walking
	sitting	sitting

Example – 3 activities / 300 instances

Confusion Matrix

Recognition

	step down	walking	sitting			
step down	100	0	0	step down	Ground truth	Σ 100
walking	5	95	0	walking		Σ 100
sitting	7	3	90	sitting		Σ 100
Σ 112	Σ 98	Σ 90				Σ 300

What is recognition accuracy over all classes?

Recognition

step down	walking	sitting			
100	0	0	step down	Ground truth	Σ 100
5	95	0	walking		Σ 100
7	3	90	sitting		Σ 100
Σ 112	Σ 98	Σ 90			Σ 300

- recognition performance averaged over all activities

$$\text{classification accuracy} = \frac{\text{correct recognized instances}}{\text{total count of instances}} = \frac{100 + 95 + 90}{300} = 95\%$$

What is recognition performance of activity “step down”?

- Recognition performance as binary problem e.g. „step down“ or „not step down“
- represented in a tuple of two elements “AB”
 - B: can be Positive (P) or Negative (N)
 - Positive (P): classifier recognizes “step down”
 - Negative (N): classifier detects “not step down”, e.g. walking was recognized instead
 - A: can be True (T) or False (F)
 - True (T): the recognition is correct
 - False (F): the recognition is not correct
- “AB” results in four combinations: TP, FP, TN, FN

Tuple combinations

Recognition			Ground truth
step down	not step down		
TP	FN	step down	
FP	TN	not step down	

- *True Positives* (TP):
 - Recognition step down (positive) and this classification is correct (true)
- *False Positives* (FP):
 - Recognition step down (positive) and this classification is incorrect (false)
- *True Negatives* (TN):
 - Recognition not step down (negative) and this classification is correct (true)
- *False Negatives* (FN):
 - Recognition not step down (negative) and this classification is incorrect (false)
- origin in Information Retrieval

What is recognition performance of activity “step down”?

Recognition

step down	not step down	not step down			
100	0	0	step down	Ground truth	Σ 100
5	95	0	not step down		Σ 100
7	3	90	not step down		Σ 100
Σ 112	Σ 98	Σ 90			Σ 300

- binary classification problem focused on activity “step down”
 - **TP** = ?

What is recognition performance of activity “step down”?

Recognition

step down	not step down	not step down			
100	0	0	step down	Ground truth	Σ 100
5	95	0	not step down		Σ 100
7	3	90	not step down		Σ 100
Σ 112	Σ 98	Σ 90			Σ 300

- binary classification problem focused on activity “step down”
 - **TP** = 100
 - **FP** = ?

What is recognition performance of activity “step down”?

Recognition

step down	not step down	not step down			
100	0	0	step down	Ground truth	Σ 100
5	95	0	not step down		Σ 100
7	3	90	not step down		Σ 100
Σ 112	Σ 98	Σ 90			Σ 300

- binary classification problem focused on activity “step down”
 - **TP** = 100
 - **FP** = 5+7 = 12
 - **TN** = 95+0+3+90 = 188
 - **FN** = ?

What is recognition performance of activity “step down”?

Recognition

step down	not step down	not step down			
100	0	0	step down	Ground truth	Σ 100
5	95	0	not step down		Σ 100
7	3	90	not step down		Σ 100
Σ 112	Σ 98	Σ 90			Σ 300

- binary classification problem focused on activity “step down”
 - **TP** = 100
 - **FP** = 5+7 = 12
 - **TN** = 95+0+3+90 = 188
 - **FN** = 0+0 = 0

Precision

The precision, often referred to *positive predictive value*, represents the ratio of correctly classified (truly) “step down” instances to the total number of instances recognized as “step down”.

Therefor the precision expresses the “step down” detection accuracy.

↓ precision Recognition				
step down	not step down	not step down		
100	0	0	step down	Σ 100
5	95	0	not step down	Σ 100
7	3	90	not step down	Σ 100
Σ 112	Σ 98	Σ 90		Σ 300

$$Precision = \frac{TP}{(TP + FP)}$$

step down (not step down e.g. walking or sitting)
 precision = $100 / (100 + 12) = 89.3\%$

Recall

The recall, also called *true positive rate* or *hit rate* represents the ratio of correctly classified “step down” instances to the total number of “step down” instances, i.e. how many of the truly “step downs” were correctly classified.

The recall represents the usability of the detection as a low usability leads to high rate of undetected “step downs”.

↓ precision
Recognition

	step down	not step down	not step down				
	100	0	0	step down	Ground truth	Σ 100	← recall
	5	95	0	not step down	Σ 100		
	7	3	90	not step down	Σ 100		
	Σ 112	Σ 98	Σ 90			Σ 300	

$$Recall = \frac{TP}{(TP + FN)}$$

step down (not step down e.g. walking or sitting)
 recall = 100 / (100+0) = 100.0%

F-measure

$$F = \frac{2 * (Precision * Recall)}{(Precision + Recall)}$$

↓ precision Recognition					
step down	not step down	not step down			
100	0	0	step down	Ground truth	Σ 100 ← recall
5	95	0	not step down		Σ 100
7	3	90	not step down		Σ 100
Σ 112	Σ 98	Σ 90			Σ 300

step down (not step down e.g. walking or sitting)

precision = 100 / (100+12) = 89.3%

recall = 100 / (100+0) = 100.0%

F-measure = 2 * (89.3% * 100.0%) / (89.3% + 100.0%) = 94.3%

Metrics summary



↓ precision
Recognition

step down	not step down	not step down			
100	0	0	step down	Σ 100	← recall
5	95	0	not step down	Σ 100	
7	3	90	not step down	Σ 100	
Σ 112	Σ 98	Σ 90		Σ 300	

Ground truth

step down (not step down e.g. walking or sitting)

precision	$= 100 / (100+12) =$	89.3%
recall	$= 100 / (100+0) =$	100.0%
F-measure	$= 2 * (89.3\% * 100.0\%) / (89.3\% + 100.0\%) =$	94.3%

walking (not walking e.g. step down or sitting)

precision	$= 95 / (95+3) =$	96.9%
recall	$= 95 / (95+5) =$	95.0%
F-measure	$= 2 * (96.9\% * 95.0\%) / (96.9\% + 95.0\%) =$	96.0%

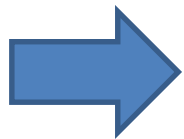
sitting (not sitting e.g. step down or walking)

precision	$= 90 / (90+0) =$	100.0%
recall	$= 90 / (90+10) =$	90.0%
F-measure	$= 2 * (100.0\% * 90.0\%) / (100.0\% + 90.0\%) =$	94.7%

Instance-based evaluation

- An instance (or frame) is a fixed-length, fixed-rate unit of time
- Instance by instance comparison between prediction (i.e. recognition) and ground truth (i.e. labels)
- Does not consider specific error types of continuous activity recognition

- Challenges detecting real world activities
 - Activities can have variable durations and ambiguous start and stop times, so that activities are being detected before or after they actually occur
 - Single events being fragmented into multiple smaller events of the same activity
 - Merging of several real events into a single recognized event



Event-based Evaluation (Ward et al. [2])

- An *event* is a variable duration sequence of positive instances within a continuous time series (i.e. a sequence of the same instances)

Instances

- step down
- walking
- walking
- walking
- sitting
- walking
- ...



Events

- step down
- walking
- sitting
- walking
- ...

- A *segment* is a contiguous sequence of instances with a variable duration, in which neither prediction nor the ground truth labels changes

Event-based Evaluation

Type of Errors



- Ground truth Errors
 - Fragmentation
 - Deletion
 - Underfill
- Recognition Errors
 - Merge
 - Insertion
 - Overfill

Event-based Evaluation - Ground truth Errors

- Fragmentation (F): A ground truth event that contains more than one matching segment

Ground truth	Recognition
step down	step down
walking	walking
walking	sitting
walking	walking
sitting	sitting
walking	walking
...	...

Event-based Evaluation - Ground truth Errors

- Deletion (D): A ground truth event that contains no matching segments

Ground truth	Recognition
step down	step down
walking	walking
walking	walking
walking	walking
sitting	walking
walking	walking
...	...

Event-based Evaluation - Ground truth Errors

- Underfill (U): A ground truth event not completely covered by recognition

Ground truth	Recognition
step down	step down
walking	walking
walking	walking
walking	sitting
sitting	sitting
walking	walking
...	...

Event-based Evaluation - Recognition Errors

- Merge (M): A recognized event that contains more than one matching segment

Ground truth	Recognition
step down	step down
walking	walking
walking	walking
walking	walking
sitting	walking
walking	walking
...	...

Event-based Evaluation - Recognition Errors

- Insertion (I): A recognized event that contains no matching segments

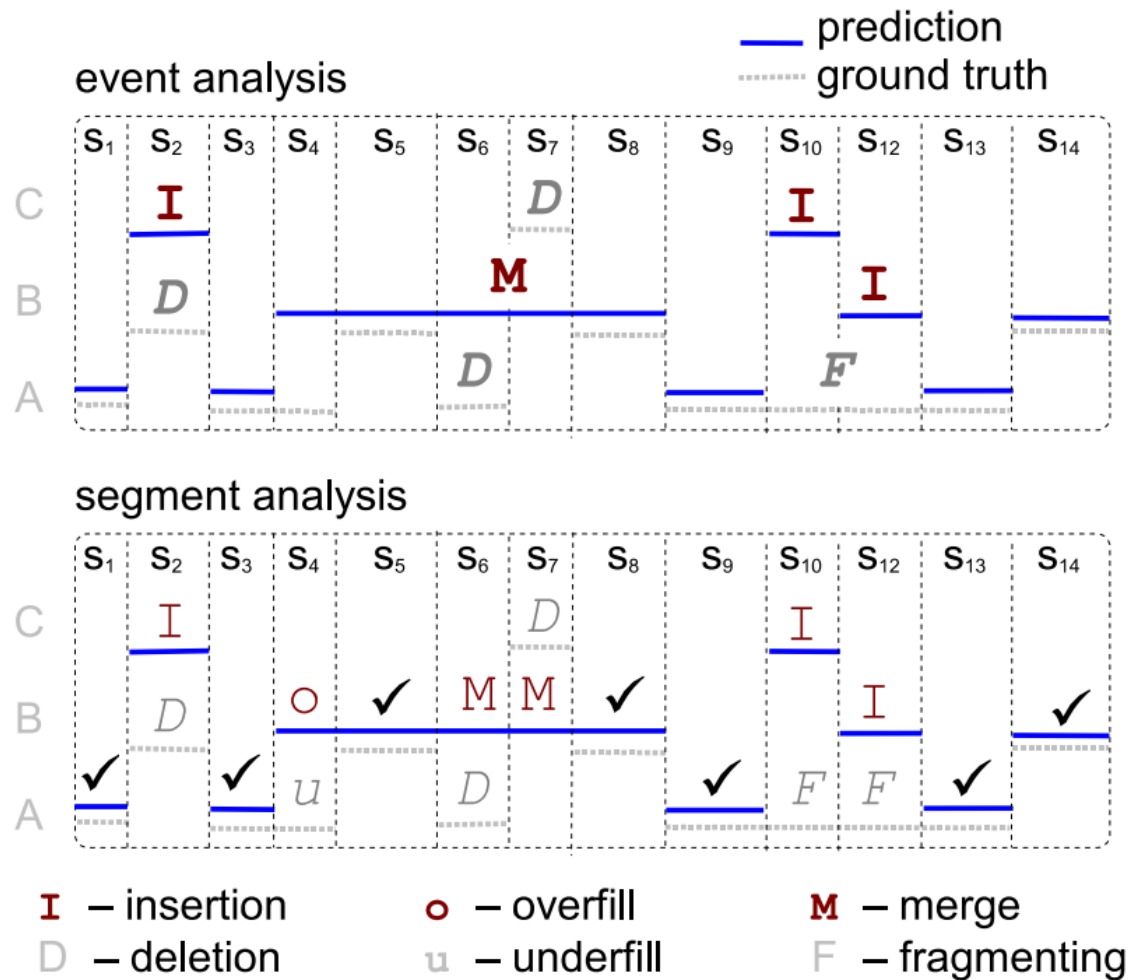
Ground truth	Recognition
step down	step down
walking	walking
walking	sitting
walking	walking
sitting	sitting
...	...
...	...

Event-based Evaluation - Recognition Errors

- Overfill (O): A recognized event which spills over its ground truth boundary

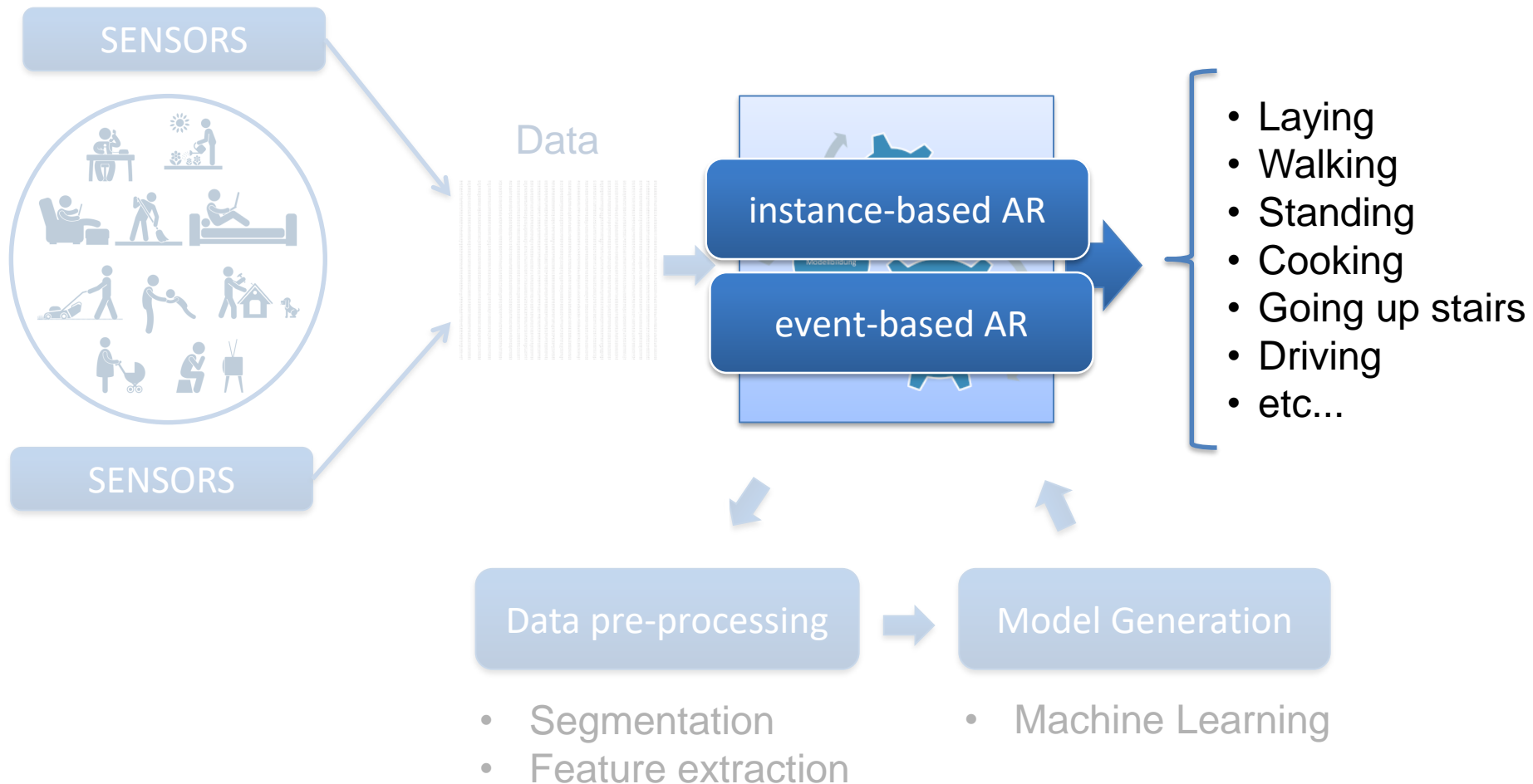
Ground truth	Recognition
step down	step down
walking	walking
walking	walking
walking	walking
sitting	walking
sitting	sitting
...	...

Example



[4]

Activity Recognition Process



Summary Questions

1. What is the purpose of activity recognition?
2. What is the difference between online and offline activity recognition?
3. What is the purpose of performance metrics?
4. Name one metric that show a models recognition performance for one activity.
5. What does the event-based evaluation help?
6. Name some errors in the event-based evaluation.

- [1] L. Bao and S. S. Intille, “Activity Recognition from User-Annotated Acceleration Data,” in Lecture Notes in Computer Science, Pervasive Computing, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, O. Nierstrasz, C. Pandu Rangan, B. Steffen, D. Terzopoulos, D. Tygar, M. Y. Vardi, and A. Ferscha, Eds, Berlin, Heidelberg: Springer Berlin Heidelberg, 2004, pp. 1–17.
- [2] J. A. Ward, P. Lukowicz, and G. Tröster, “Evaluating Performance in Continuous Context Recognition Using Event-driven Error Characterisation,” in Proceedings of the Second International Conference on Location- and Context-Awareness, Berlin, Heidelberg, 2006, pp. 239–255.
- [3] J. A. Ward, P. Lukowicz, and H. W. Gellersen, “Performance Metrics for Activity Recognition,” ACM Trans. Intell. Syst. Technol., vol. 2, no. 1, pp. 1–23, Jan. 2011.
- [4] J. A. Ward, P. Lukowicz, and G. Tröster, “A categorisation of performance errors in continuous context recognition,” in Proc. IEEE Int’l Symp. on Wearable Comp, Workshop for On-Body Sensing, 2005.