INTERACTIVE AND ACTIVE LEARNING FOR SOCIAL ROBOTICS

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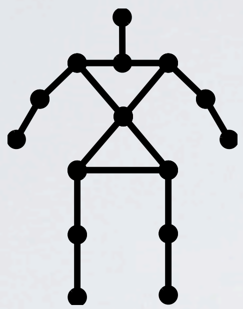
Leganés, November 2015

Introduction

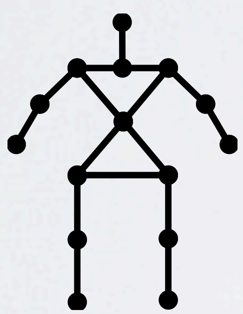
Part I: Interactive Learning



Poses

Objects

Part II: Interactive and Active Learning



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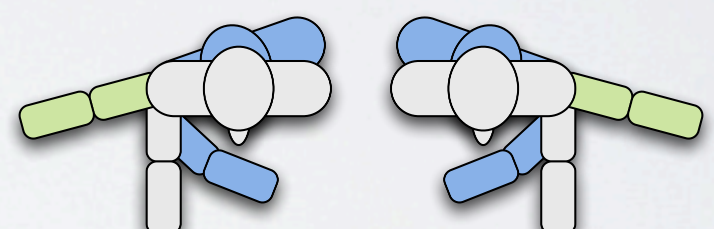

Novelties

Conclusions

INTRODUCTION

THE NEED OF LEARNING IN ROBOTICS

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HOW SHOULD ROBOTS LEARN?

HOW SHOULD ROBOTS LEARN?

OPEN CHALLENGES

Interaction During Learning	→	Generally very simple
Label acquisition	→	Complex task
Deciding when to finish the training	→	Why not let the robot take this decision?
Detecting novel concepts that require more training	→	Novelty detection in robotics

OBJECTIVES OF THE THESIS

*"To **develop a system that enables a social robot to learn interactively in a natural way**, similarly to how a person would learn from another person."*

OBJECTIVES OF THE THESIS

Multimodal Interaction for Learning

Apply Active Learning for learning new concepts

"Robot-driven" learning

- *Let the robot decie how much training does it need*
- *Enable the robot to detect new concepts*

Different domains: Pose and object recognition

RELATED WORK

Interaction in Learning. [Rybski et al., 2007]

Flexible interaction, but describe tasks, not concepts.

Active Learning. Mostly in learning skills.

[Rosenthal et al., 2009, 2012], [Cakmak and Thomaz, 2012; Cakmak et al., 2010]

AL for concept acquisition

We study the impact of innacurate user answers

RELATED WORK

Novelty Detection in robotics

- Video surveillance [Drews et al., 2013]
- Room Semantics acquisition [Pinto et al., 2011]
- *We use to detect new concepts to learn*

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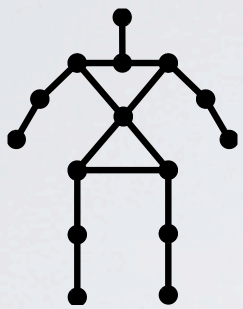

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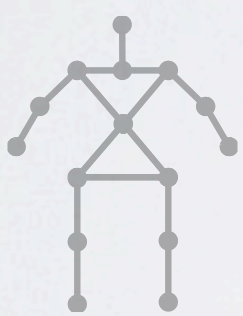

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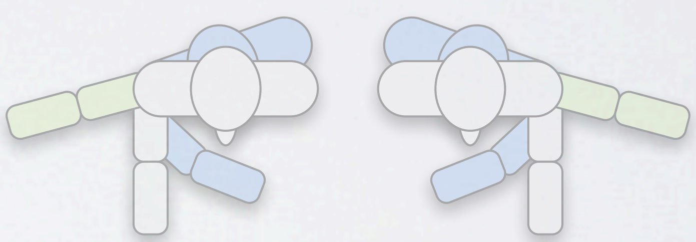

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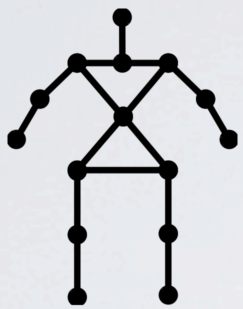

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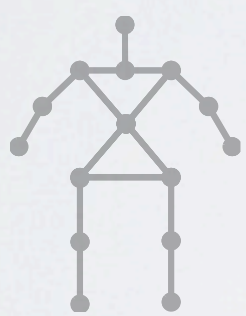

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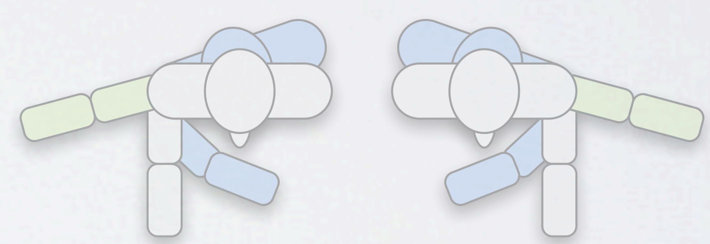

Novelties

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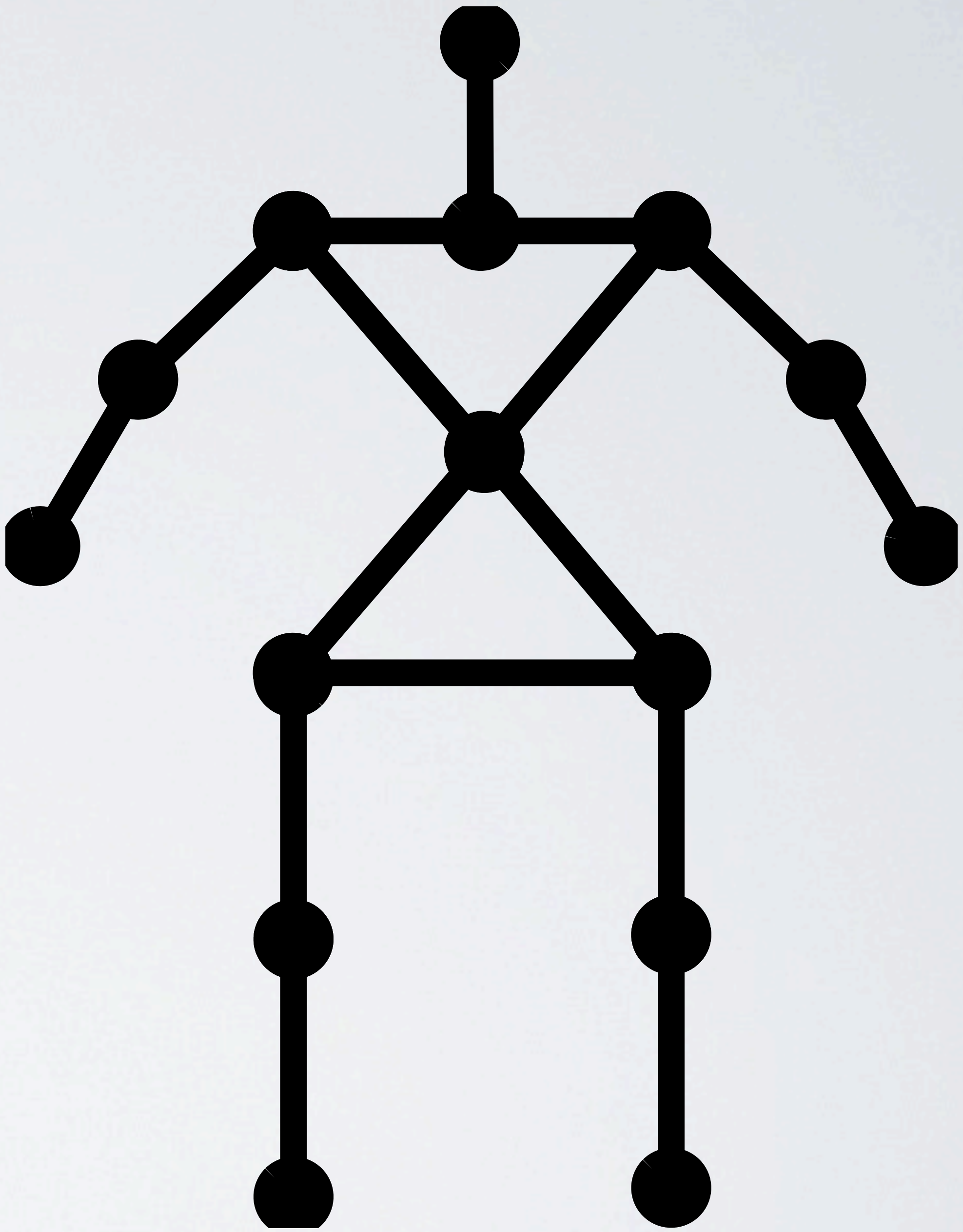
INTERACTIVE LEARNING

LEARNING POSES



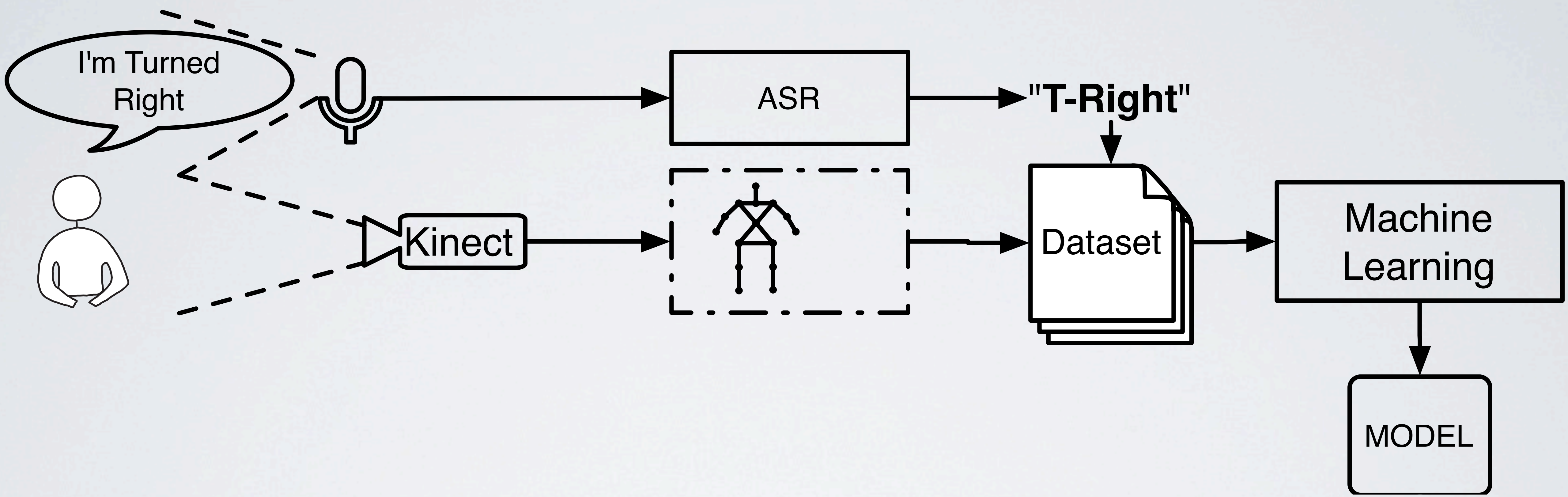
OBJECTIVE

To endow a social robot with interactive learning capabilities.

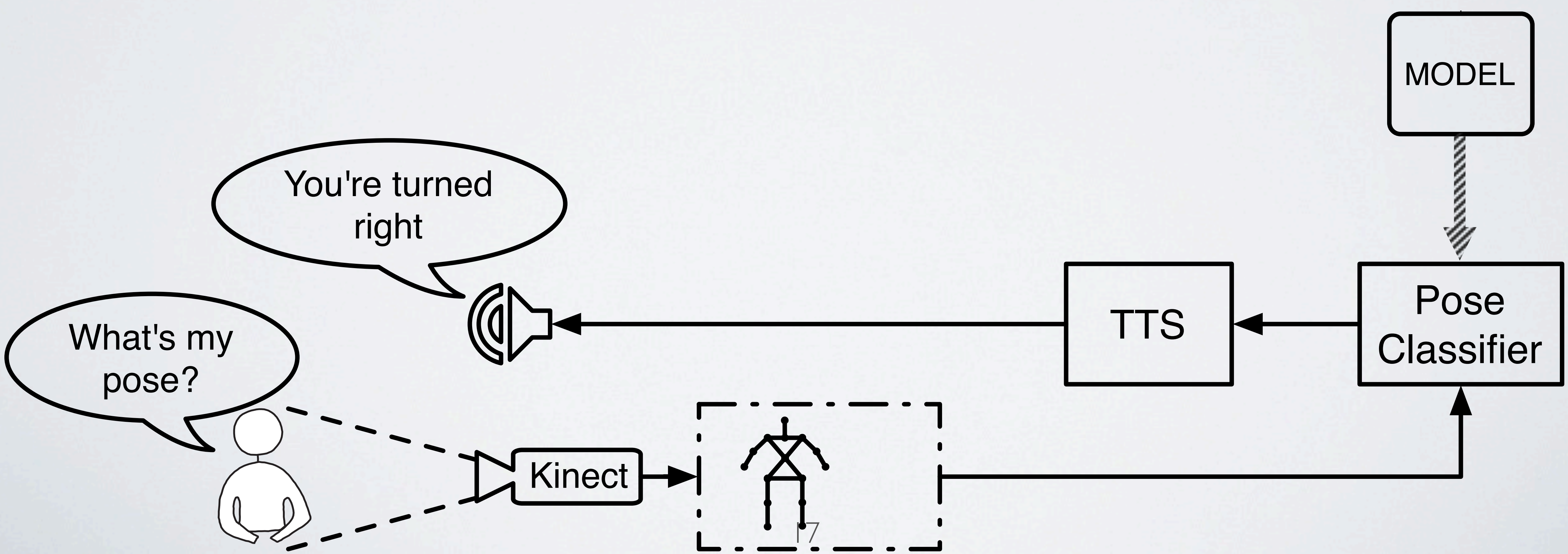
PLATFORM:

Maggie

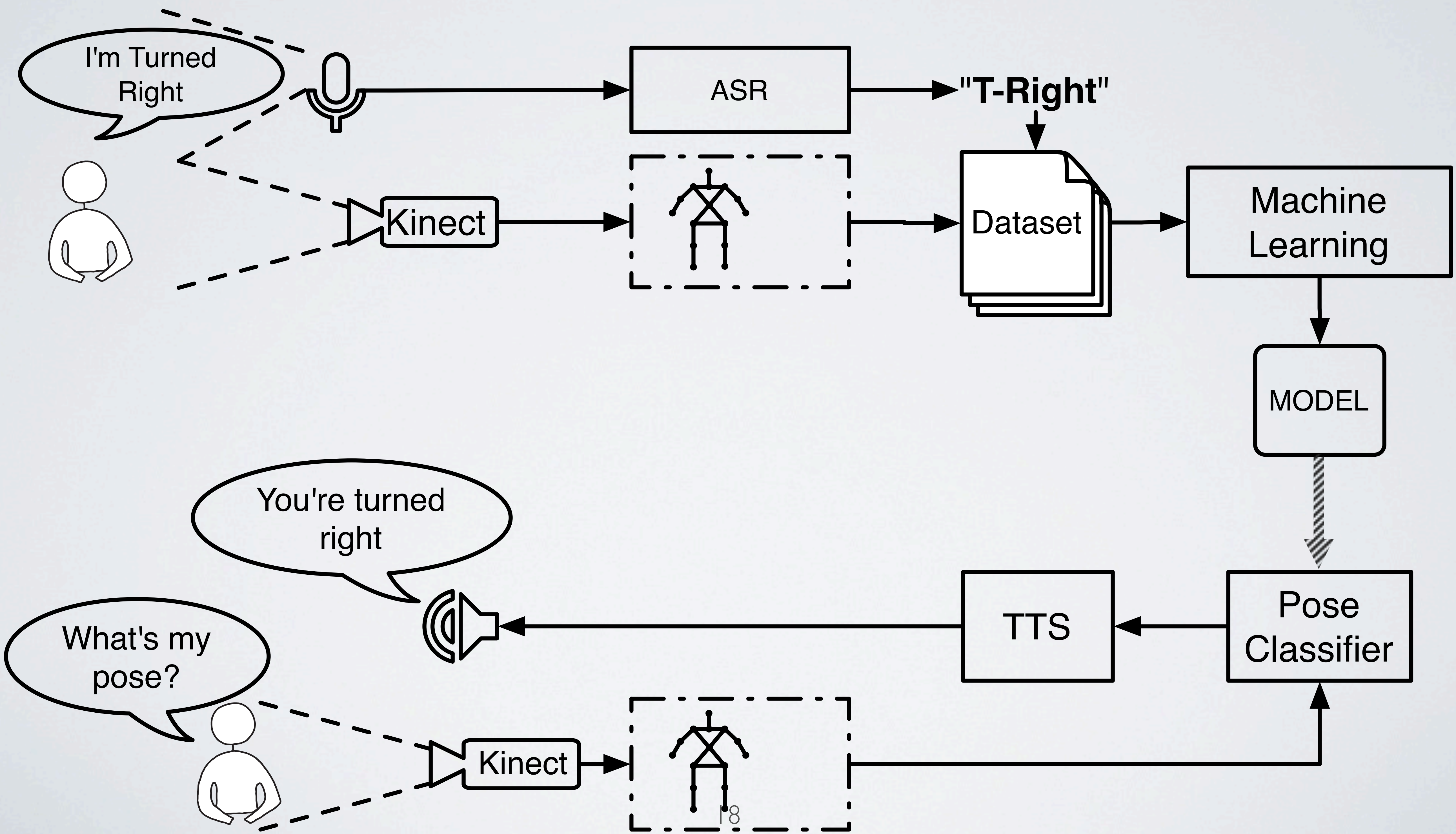
SYSTEM OVERVIEW: **TRAINING**



SYSTEM OVERVIEW: **EXPLOITATION**



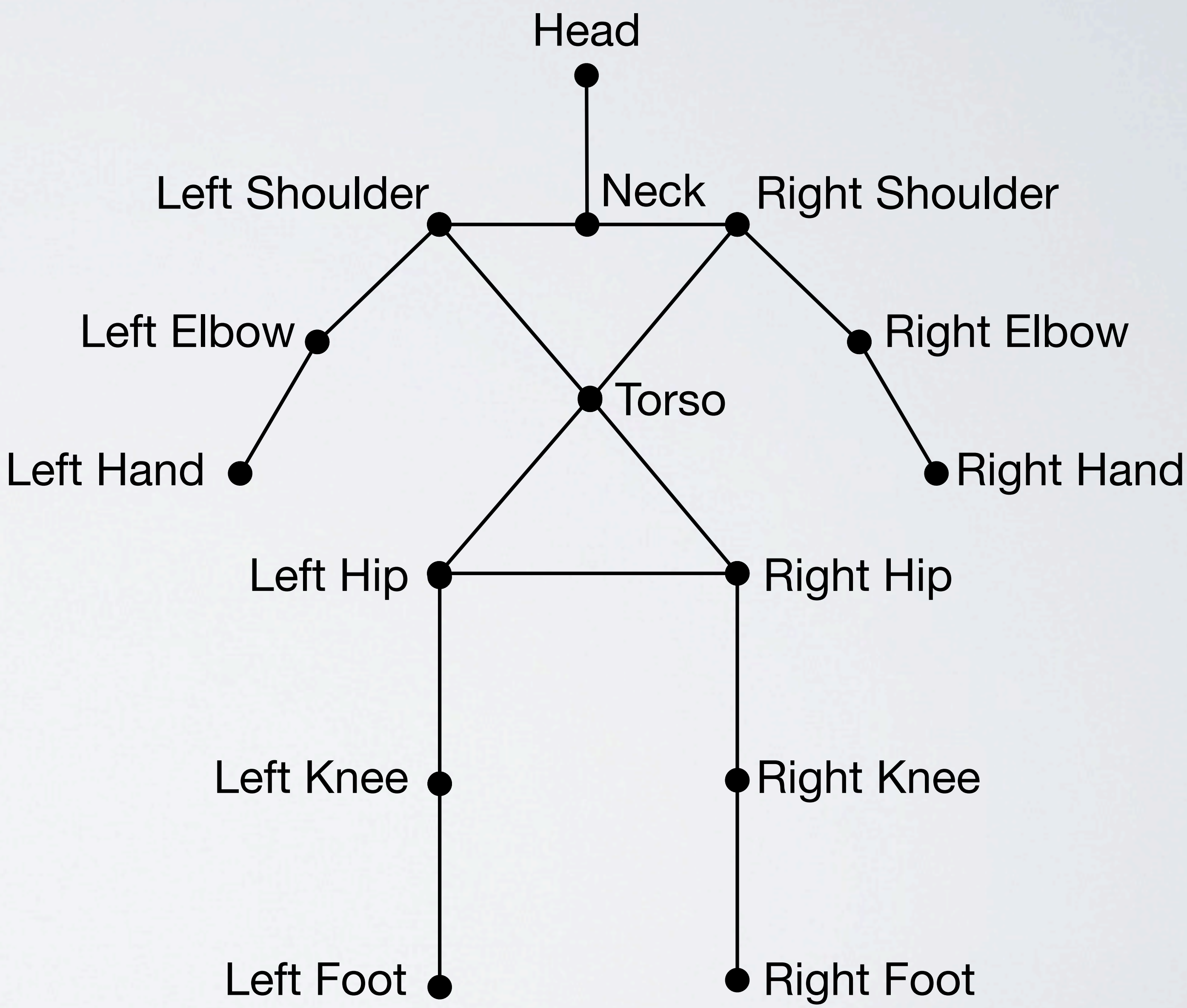
SYSTEM OVERVIEW



KINECT SKELETON MODEL

15 Joints

7 Parameters per joint:
$(x, y, z, q_x, q_y, q_z, q_w)$



GRAMMAR-BASED INTERACTION

Two different grammars:

Pose definition (up to 9 poses):

"I'm standing up, looking to my right."

"Look, Maggie. I am looking towards my right."

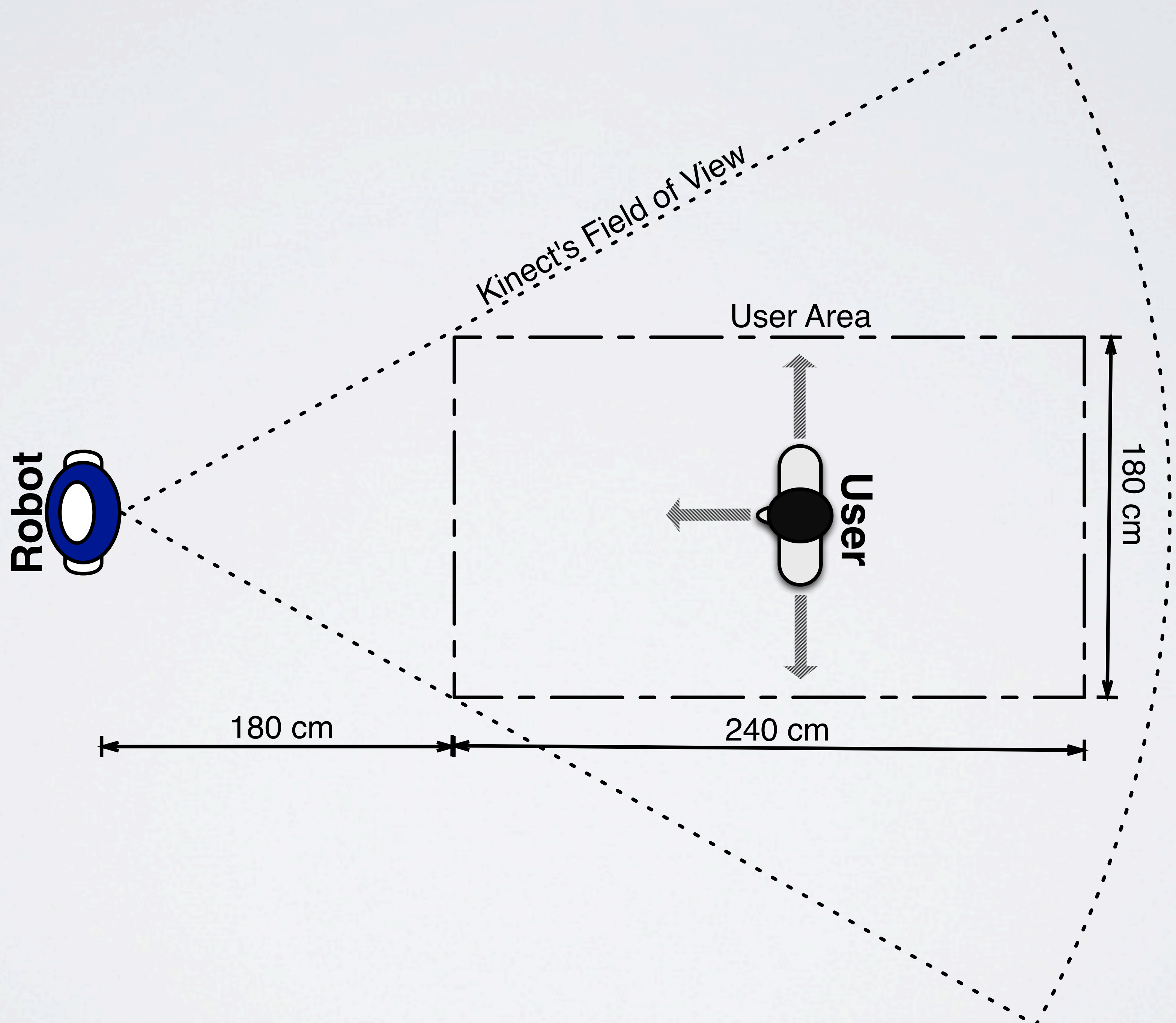
Control of the sessions/phases:

*"**Start recording** a pose."*

*"**Stop recording**."*

"End session."

SCENARIO DESCRIPTION



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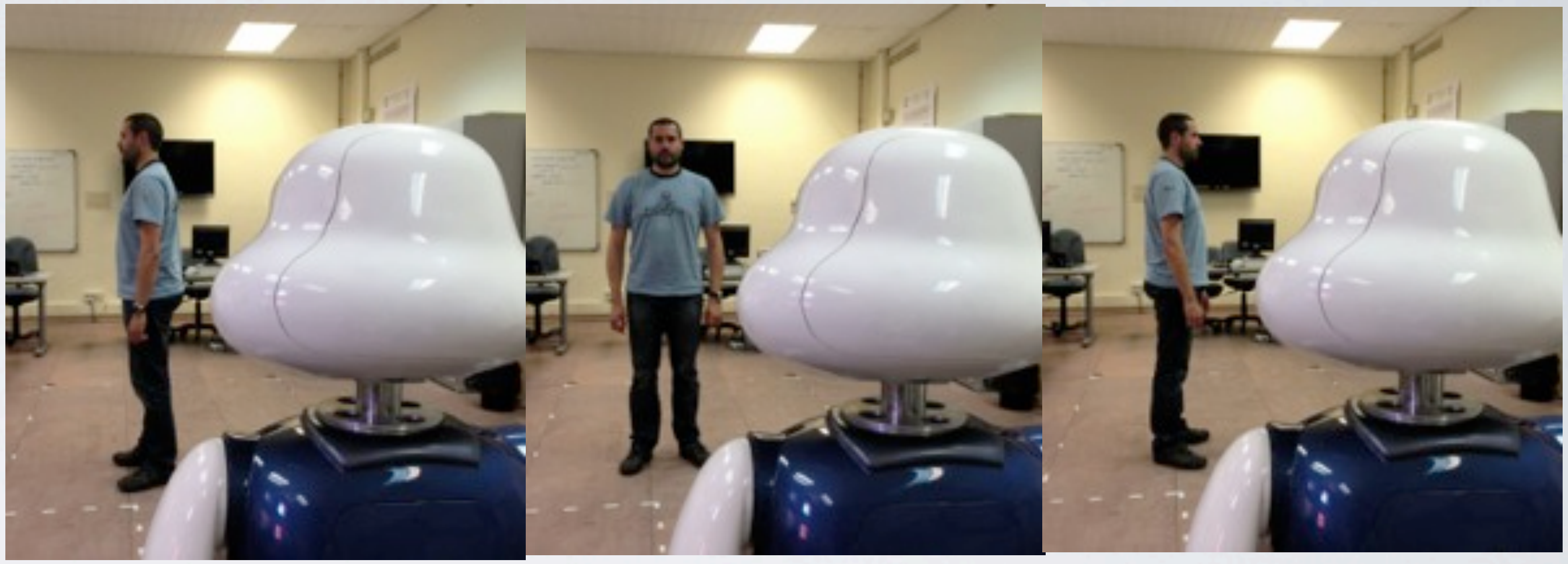

24 Training Users

Teaching 9 poses:

- Turned (L, F, R)
- Looking (L, F, R)
- Pointing (L, F, R)

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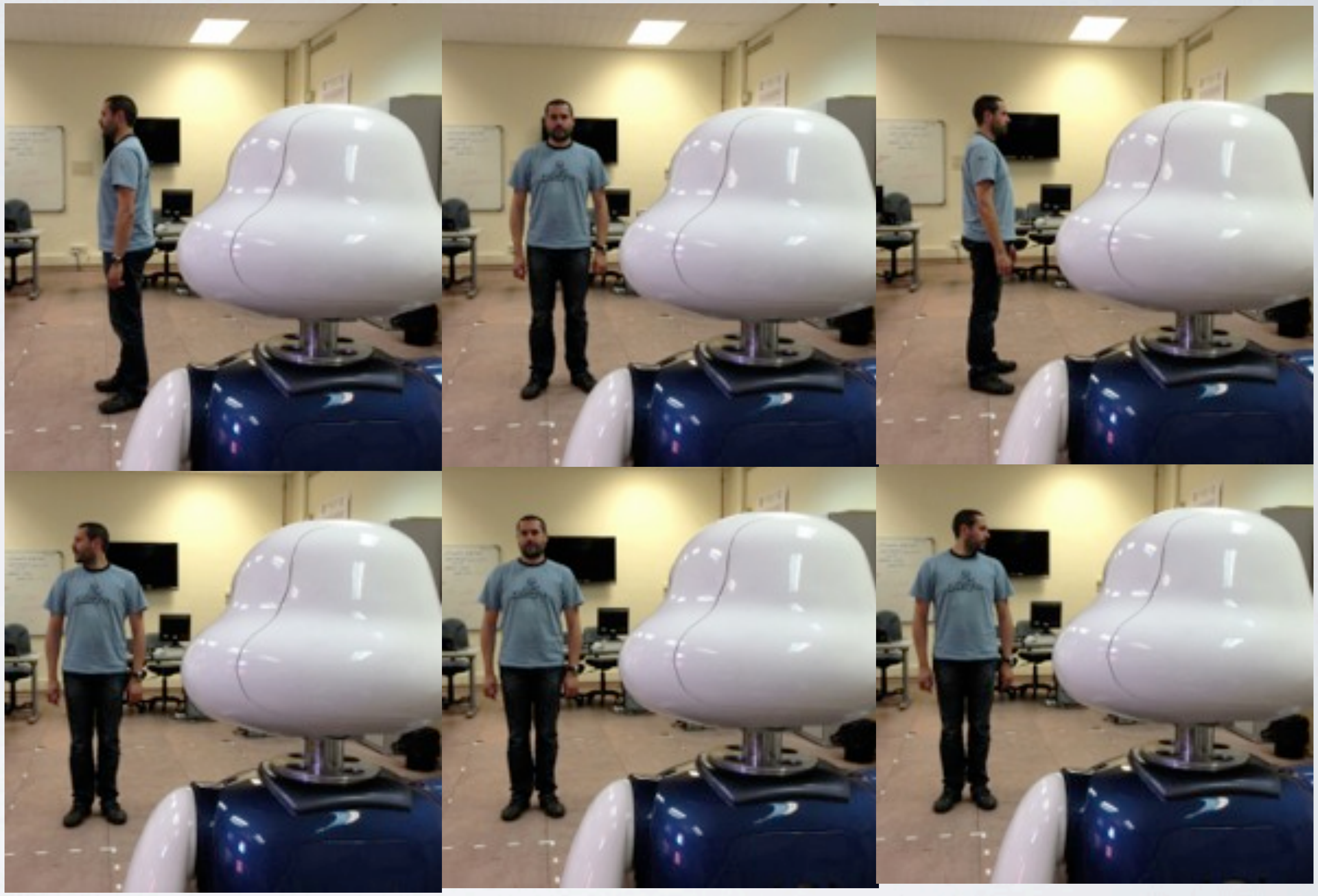

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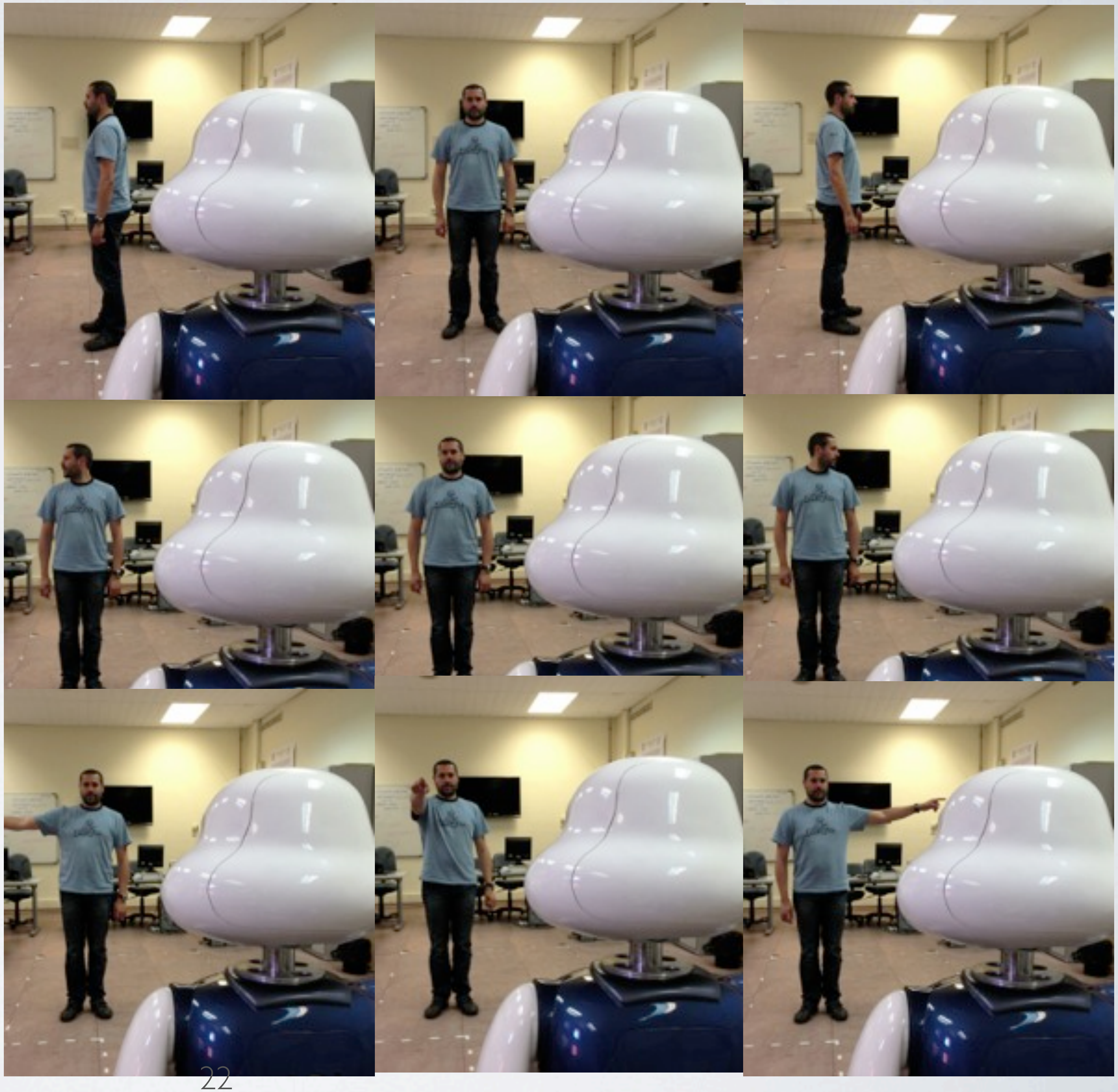
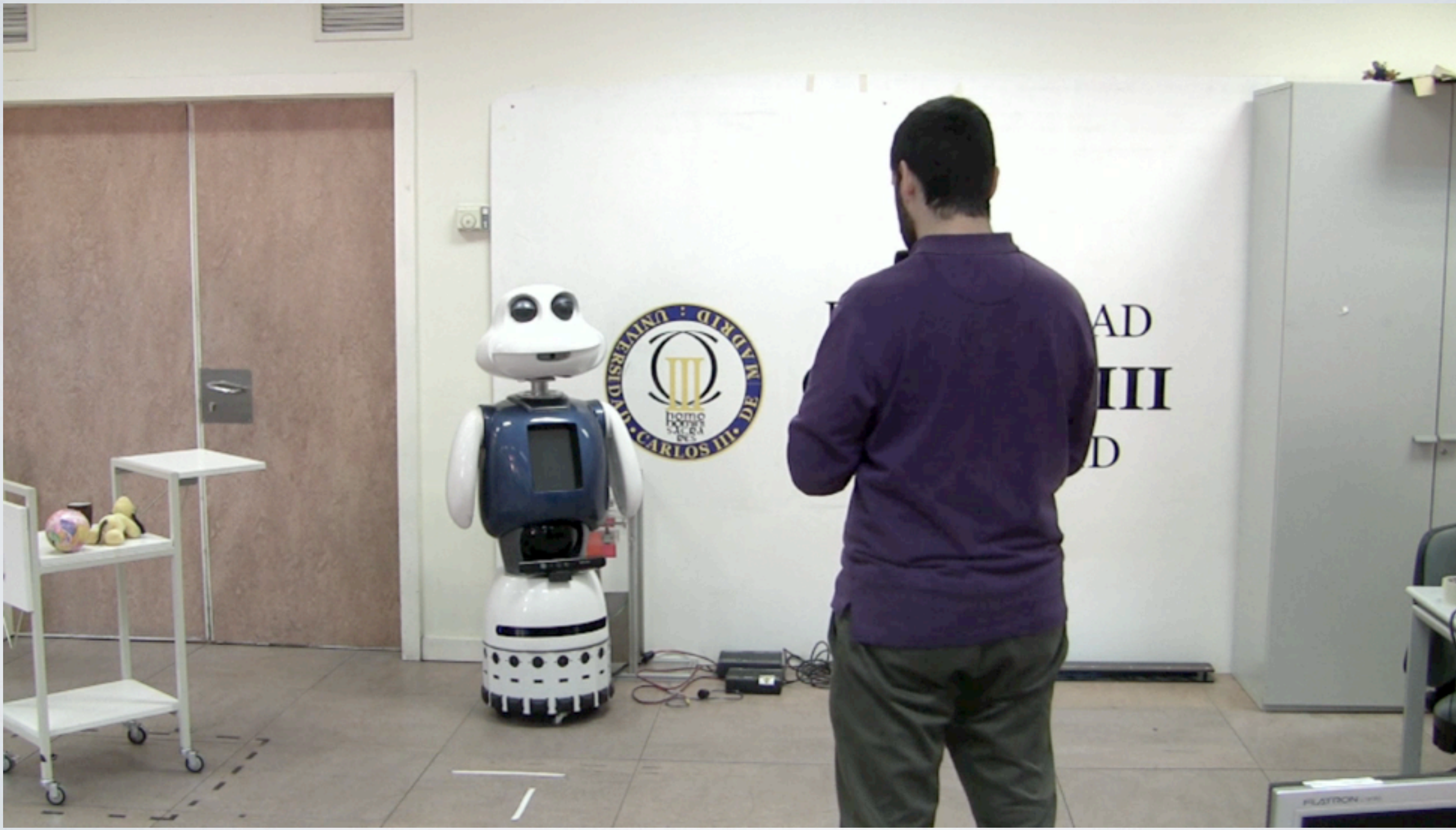
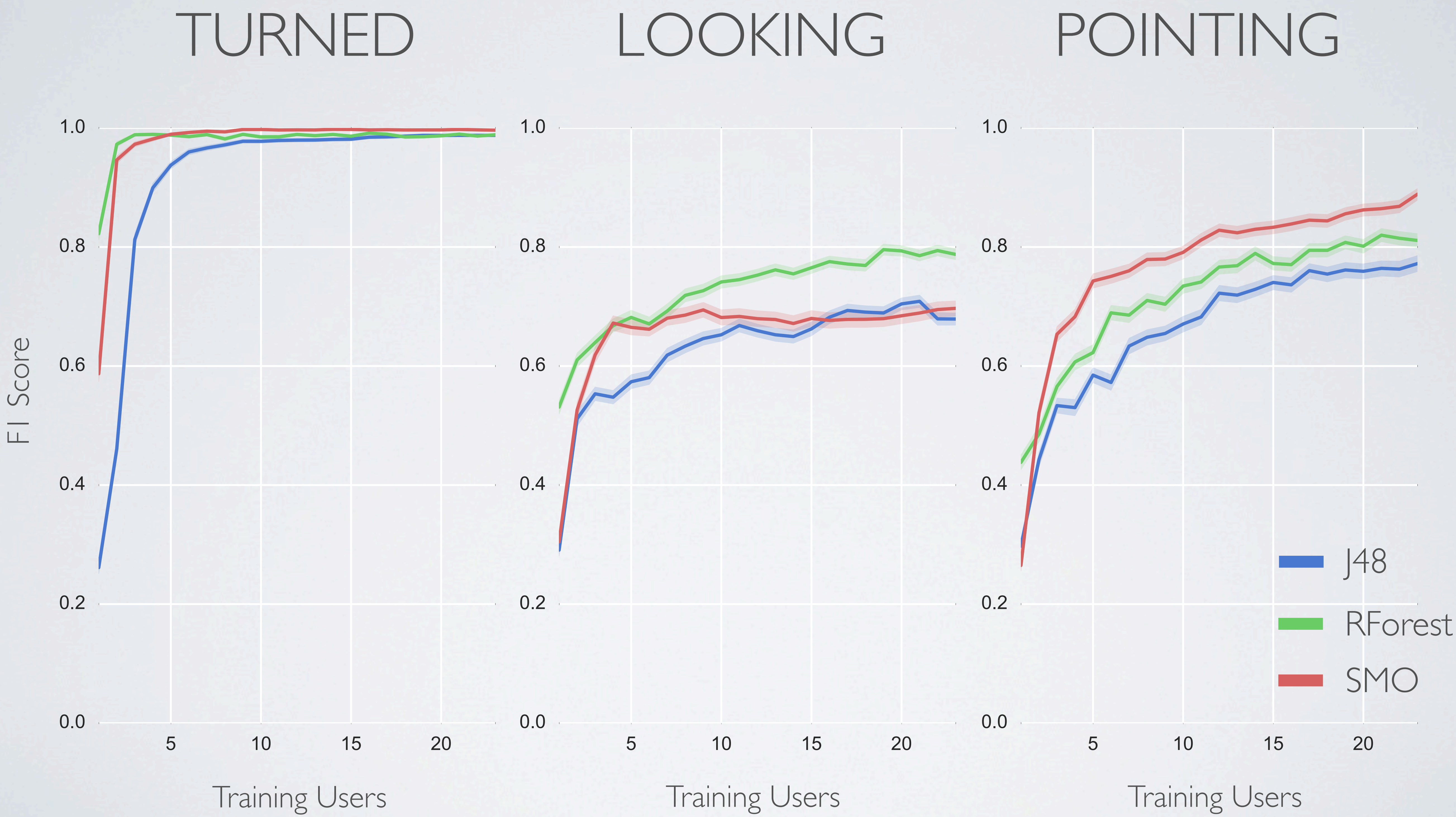


VIDEO

VIDEO



RESULTS


TURNED
LOOKING
POINTING
F1 Score
1.0
0.8
0.6
0.4
0.2
0.0
5
10
15
20
Training Users
J48
RForest
SMO

CONCLUSION

Robot is able to learn by interacting with the user.

Grammar-based interaction.

It's powerful, but a bit inflexible:

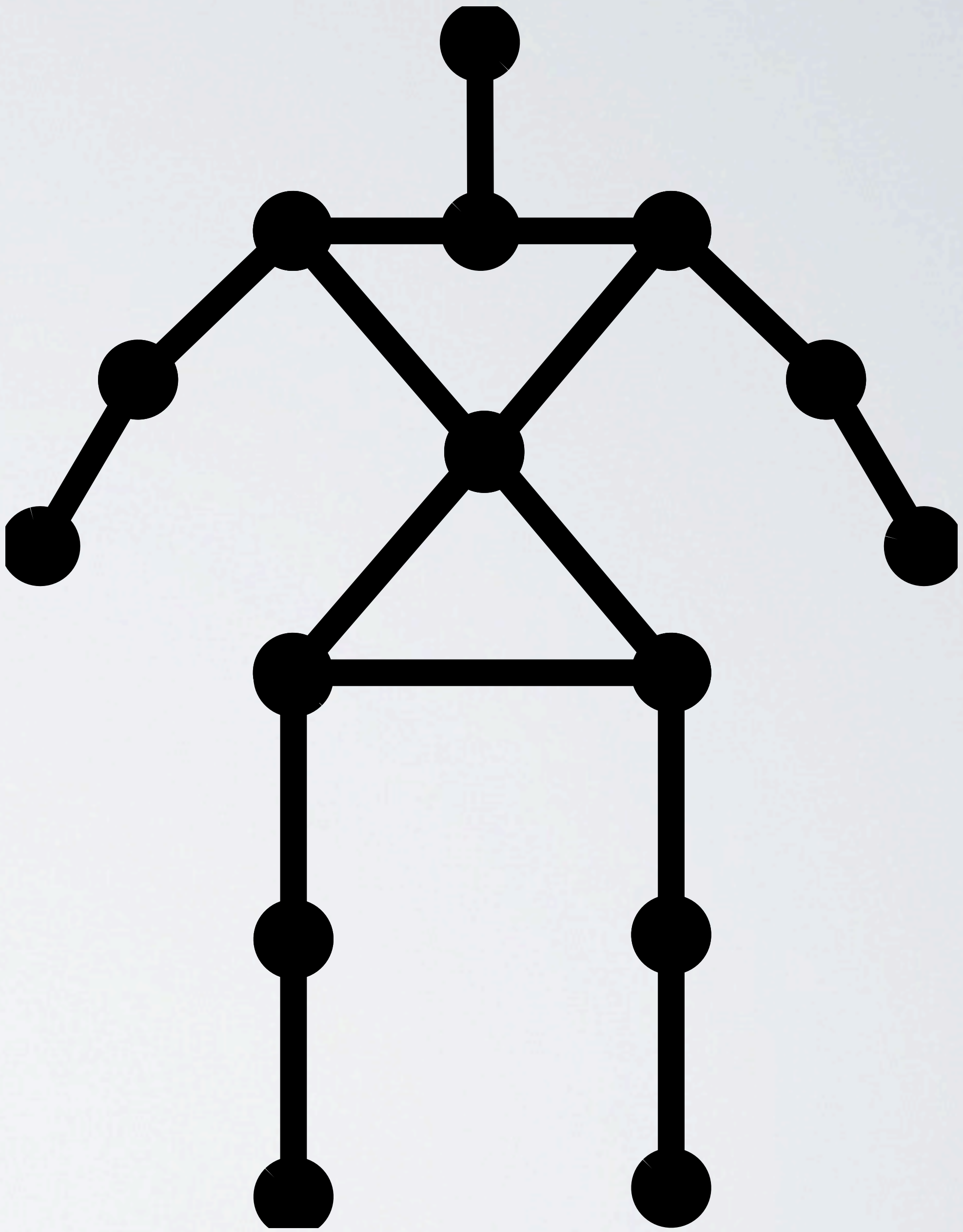
- Max. num poses set by grammar programmer

PUBLISHED RESULTS

- **V. Gonzalez-Pacheco**, M. Malfaz, F. Fernandez, and M. A. Salichs, "*Teaching human poses interactively to a social robot*," Sensors, vol. 13, no. 9, pp. 12406–12430, 2013.
- A. Ramey, **V. González-Pacheco**, and M. A. Salichs, "*Integration of a low-cost RGB-D sensor in a social robot for gesture recognition*," in Proceedings of the 6th international conference on Human-Robot Interaction - HRI '11, 2011, pp. 229–230.

INTERACTIVE LEARNING

LEARNING POSES



Introduction

Part I: Interactive Learning

Poses

Objects

Part II: Interactive and Active Learning

Poses

Objects

Novelties

Conclusions

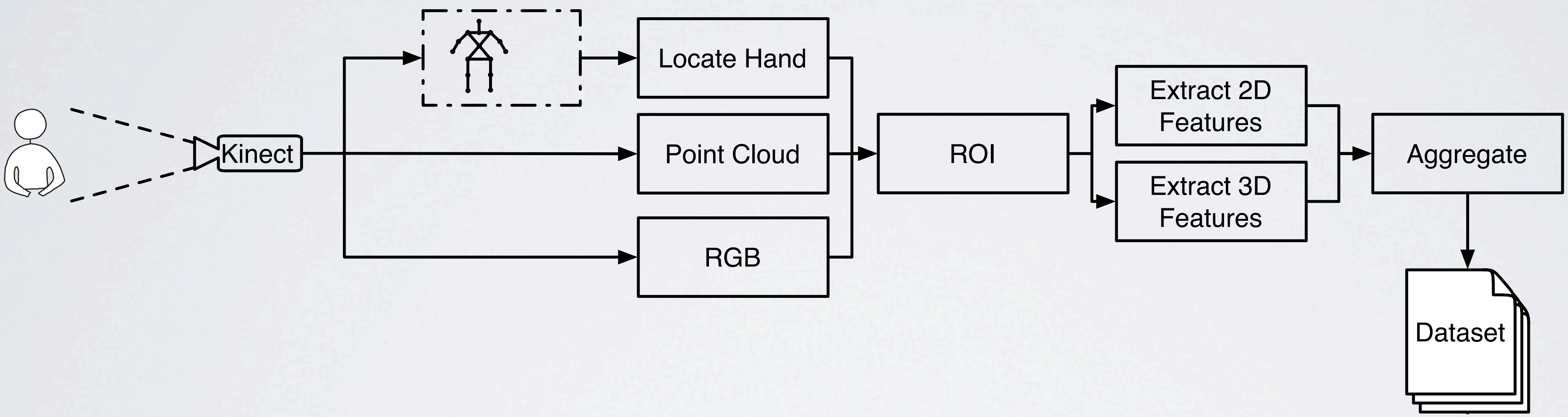
INTERACTIVE LEARNING

LEARNING OBJECTS

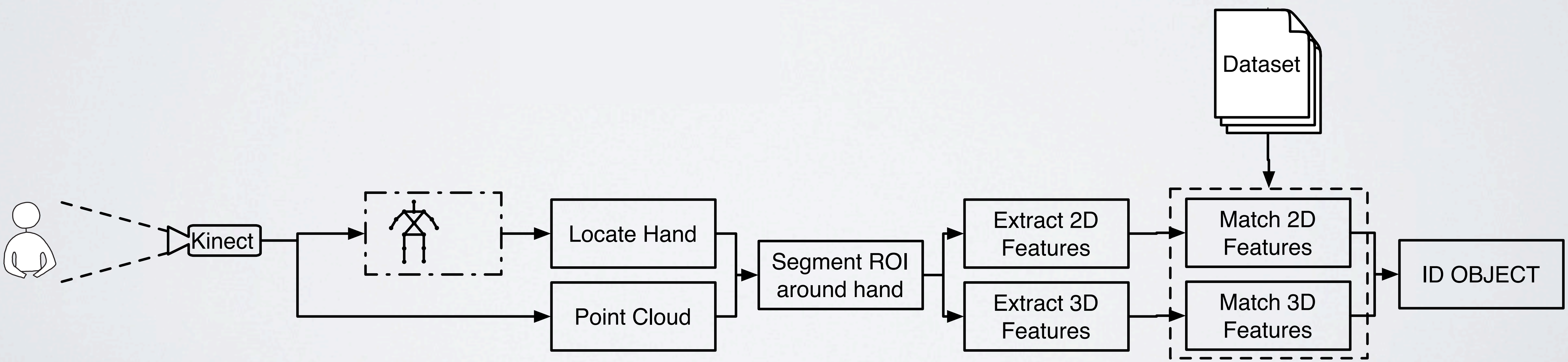
OBJECTIVE

Apply Interactive Learning in different domain:
hand-held object recognition.

SYSTEM DESCRIPTION:
TRAINING

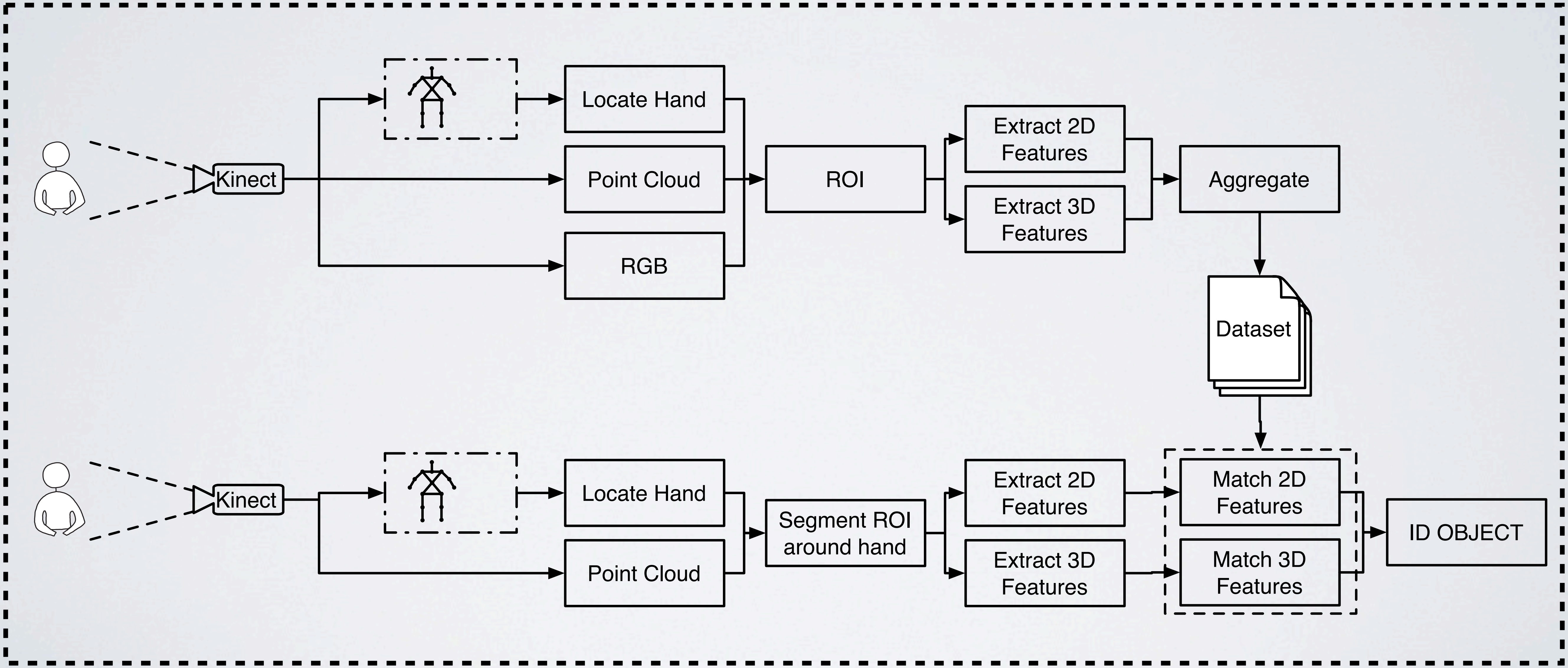


SYSTEM DESCRIPTION:
EXPLOITATION



SYSTEM DESCRIPTION

OCULAR SYSTEM



LEARNING INTERACTION

- No speech
- Arm poses:
  - Extended: learning
  - Folded: recognizing

EXPERIMENT DESCRIPTION

Room with mixed natural and artificial light

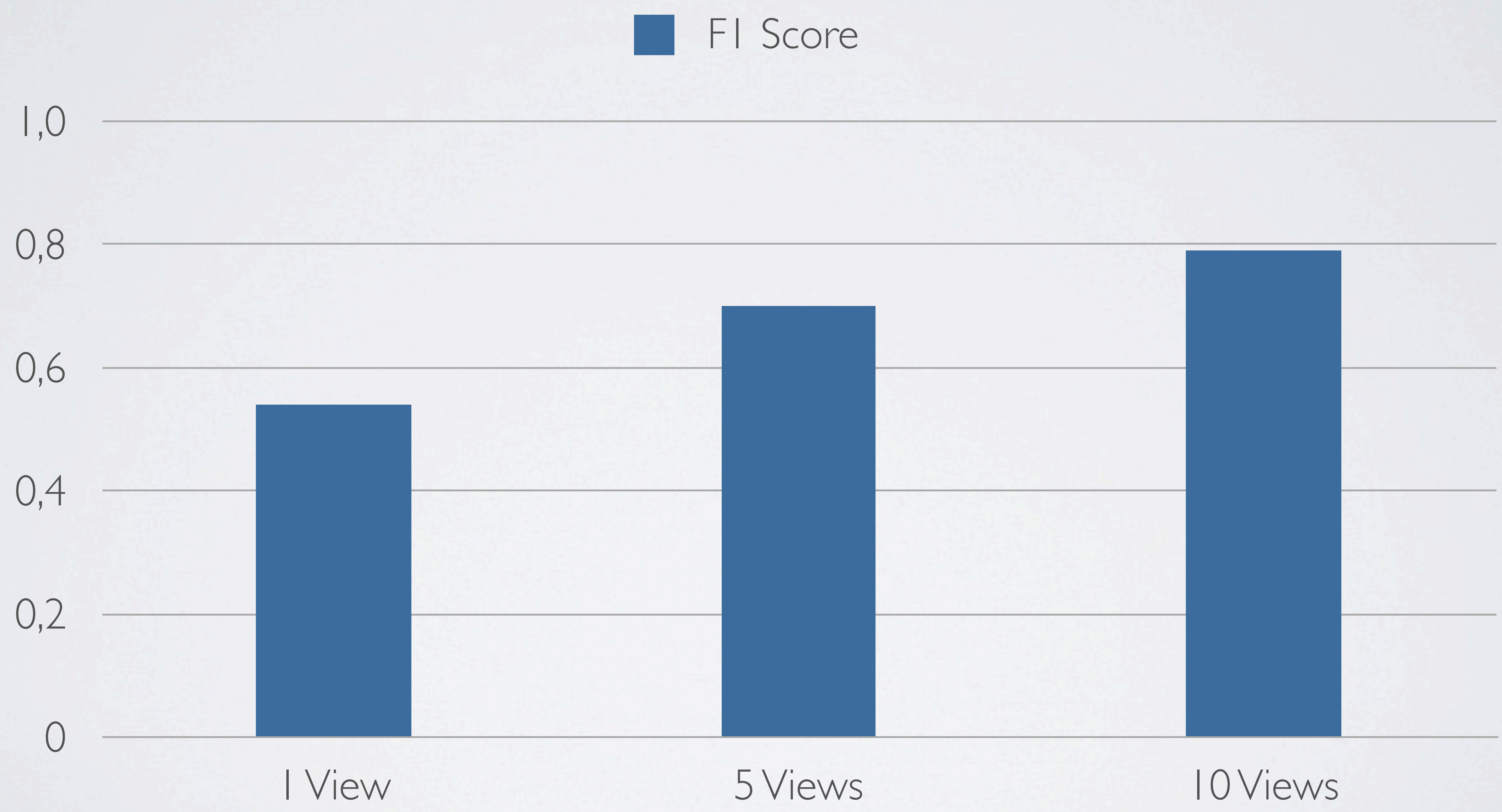
6 objects

Trained with 1, 5 and 10 views per object.

EXPERIMENT DESCRIPTION

Example of different views captured by the system

RESULTS: LEARNING CURVE



RESULTS

COMBINING MATCHERS (10 VIEWS)

	F1 Score		
Object	**RGB**	**Point Cloud**	**Combined**
ball	0.62	0.69	**0.72**
skull	0.67	0.47	**0.69**
cup	0.61	0.51	**0.77**
bottle	0.72	0.63	**0.89**
mobile	0.76	0.53	**0.82**
calculator	0.85	0.73	**0.83**
Total	0.71	0.59	**0.79**

CONCLUSION

System working in real time

RGB (2D) prediction performed better than 3D prediction

Combining both matchers improves performance

System reaches ~80% F1 Score

INTERACTIVE LEARNING

LEARNING OBJECTS

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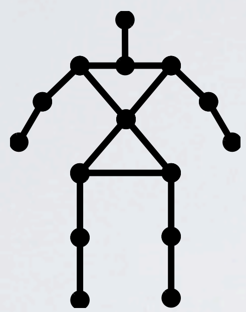
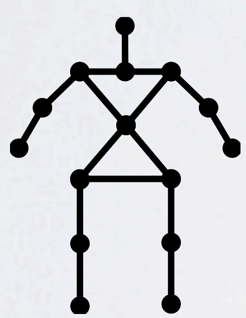


Poses

Objects

Part II: Interactive and Active Learning



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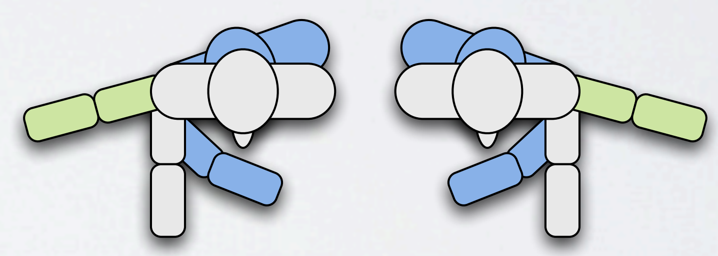

Novelties

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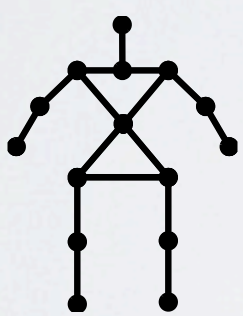

Poses

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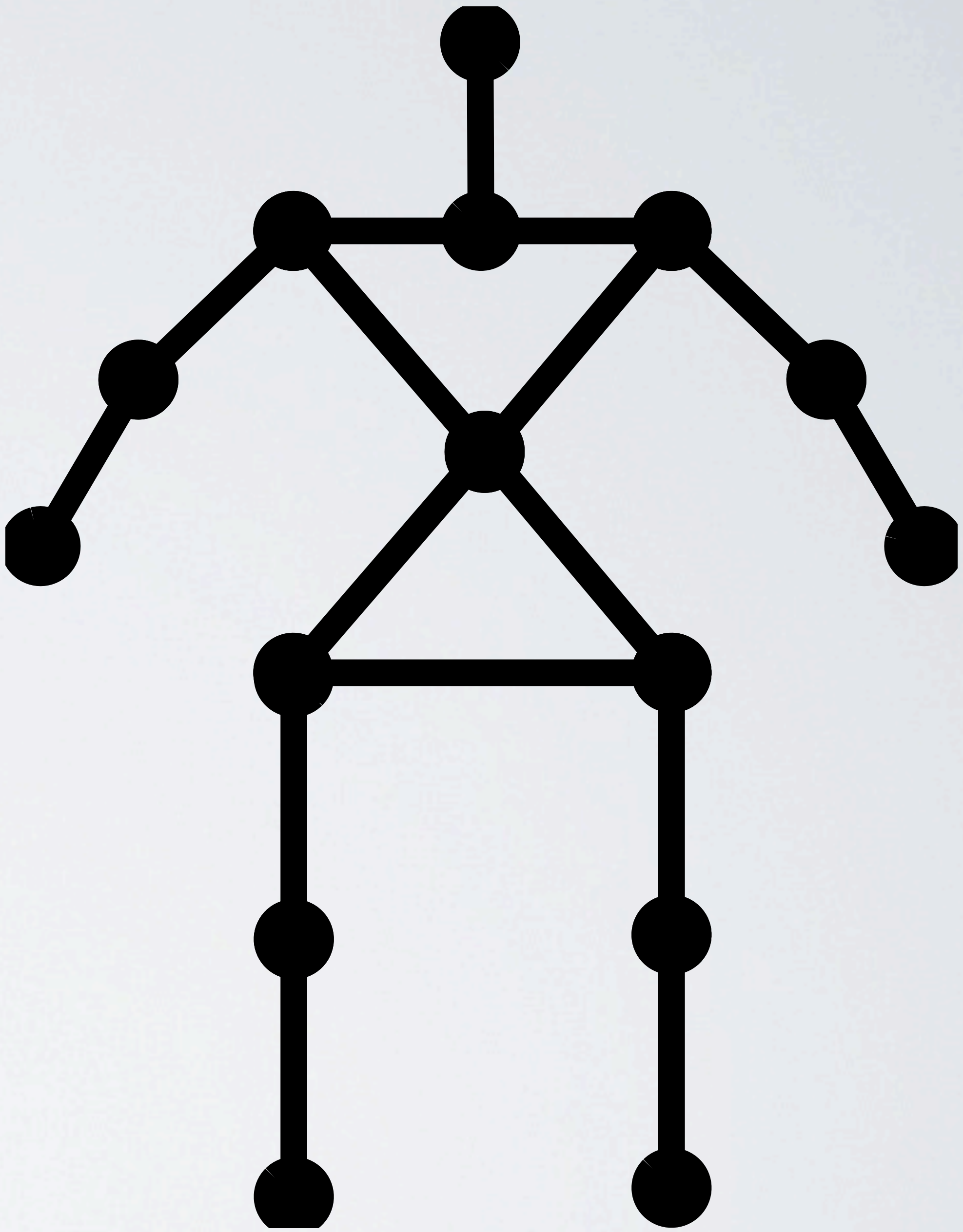
ACTIVE LEARNING

LEARNING POSES



MOTIVATION

What happens when the robot asks the human and he/she provides an innacurate answer?

OBJECTIVE

Study how the user's innacurate answers can affect robot learning

Domain: pose recognition

FROM FEATURE QUERIES...

Free Speech Queries (FSQ):

"Which is the most important limb in this pose?"

"Which limbs are important in this case?"

Yes/No Queries (YNQ):

"Is the hand important?"

"Should I pay attention to your head when you are pointing?"

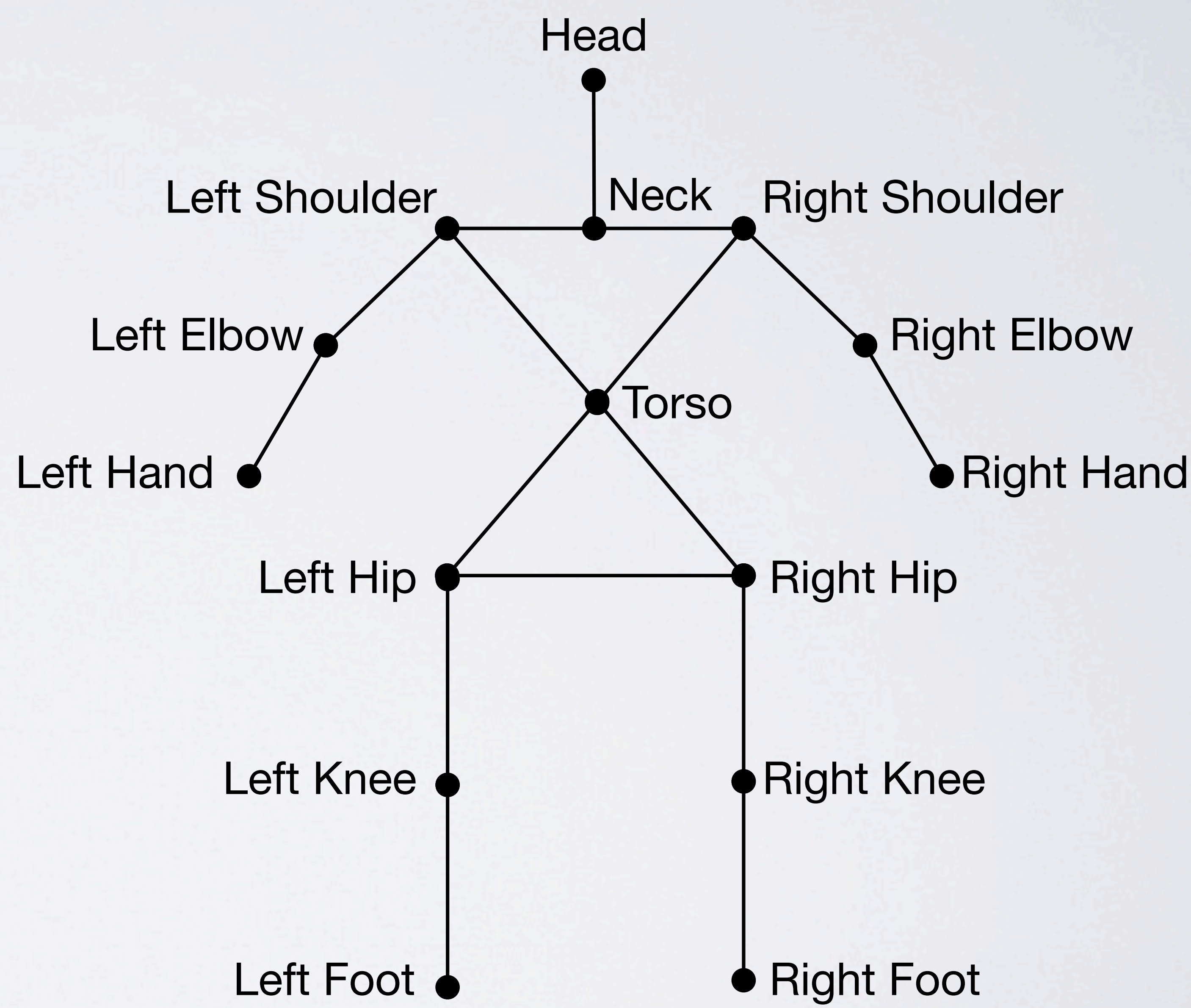
Rank Queries (RQ):

"How important is your hand?"

...TO FEATURE FILTERS

Build a Threshold (**Th**) that is averaged from different answers.

Limbs below threshold, are filtered out



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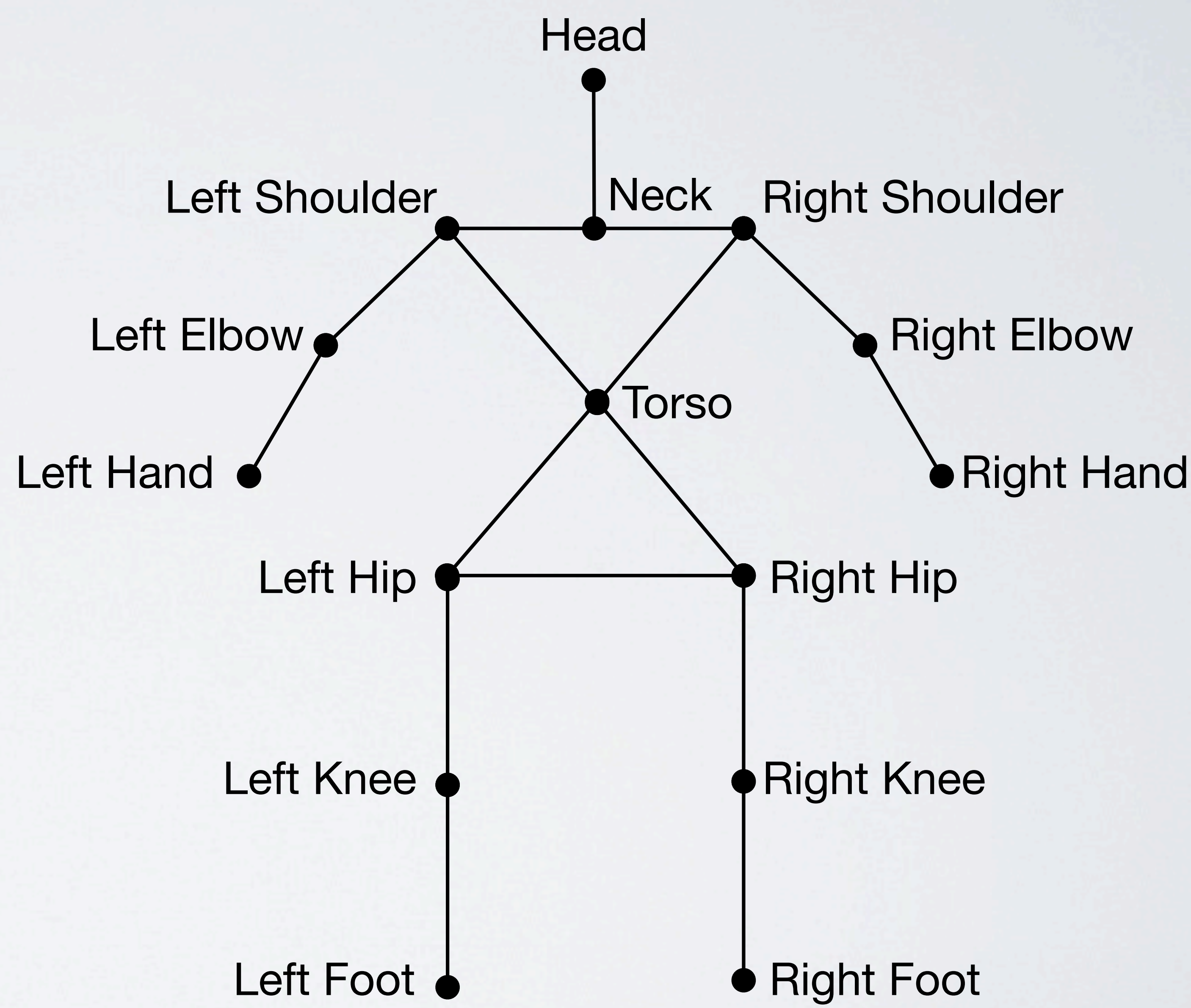
Example:



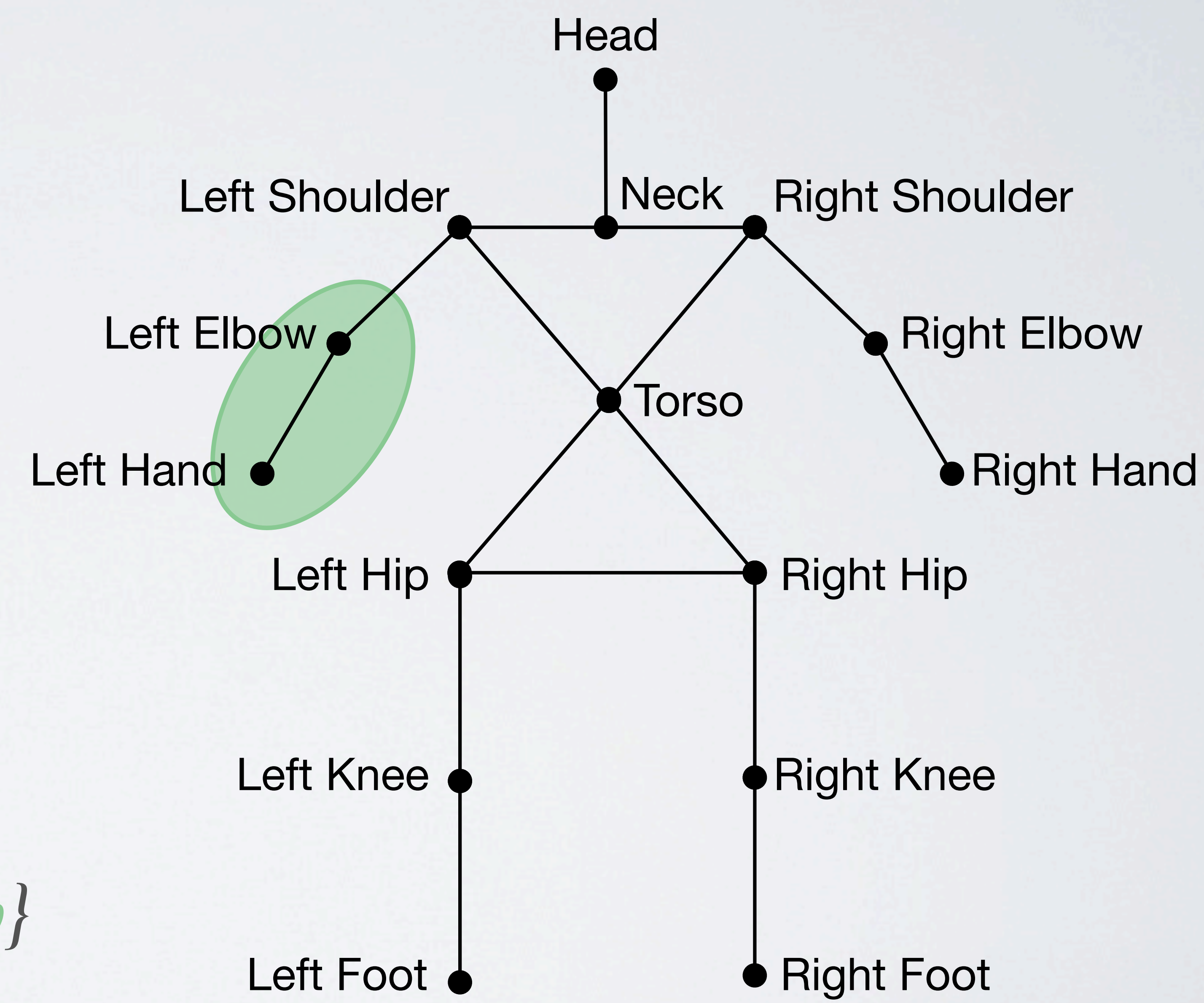
...TO FEATURE FILTERS

Build a Threshold (**Th**) that is averaged from different answers.

Limbs below threshold, are filtered out

Example:

Users selected: {*hand*, *elbow*}



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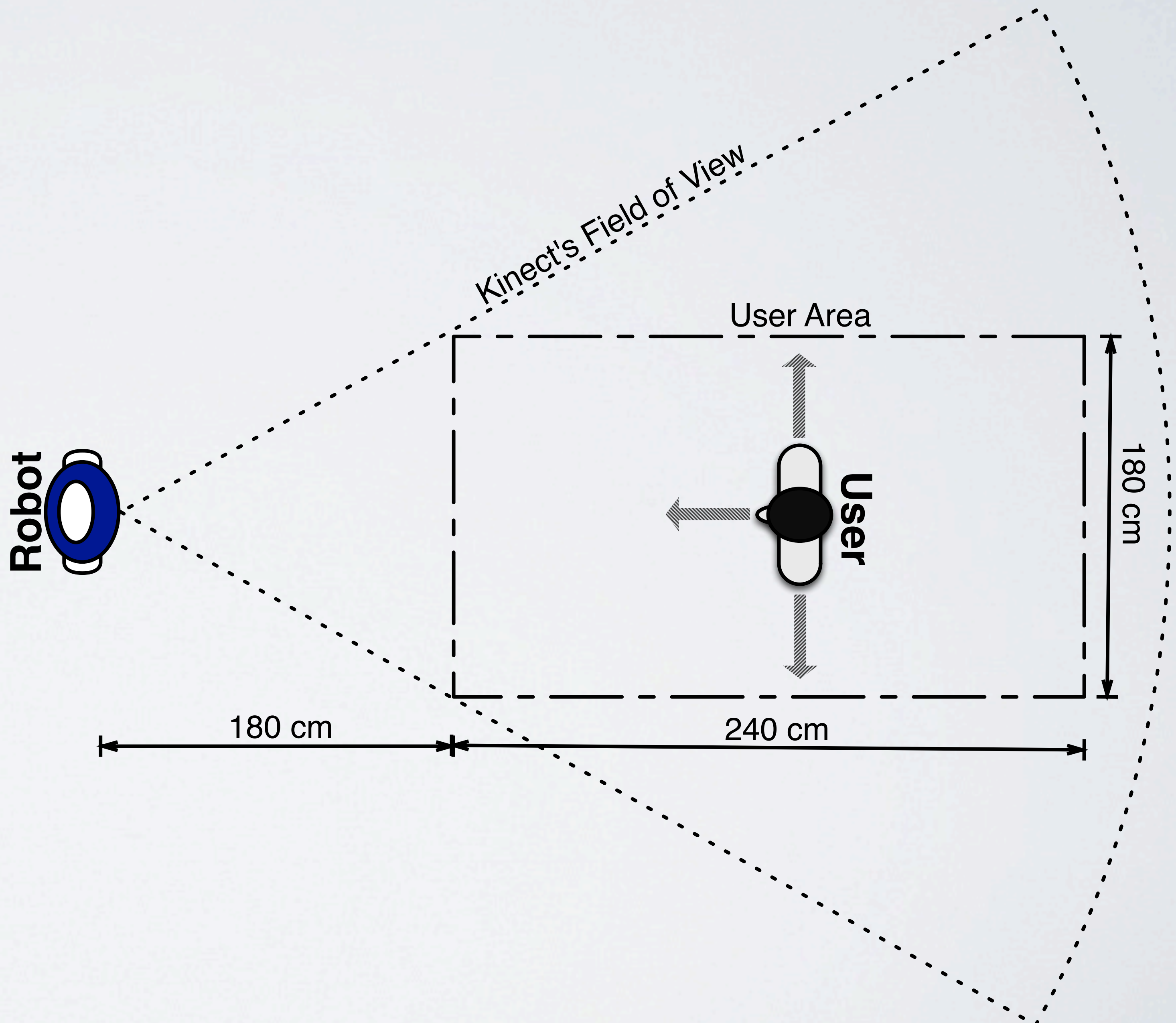
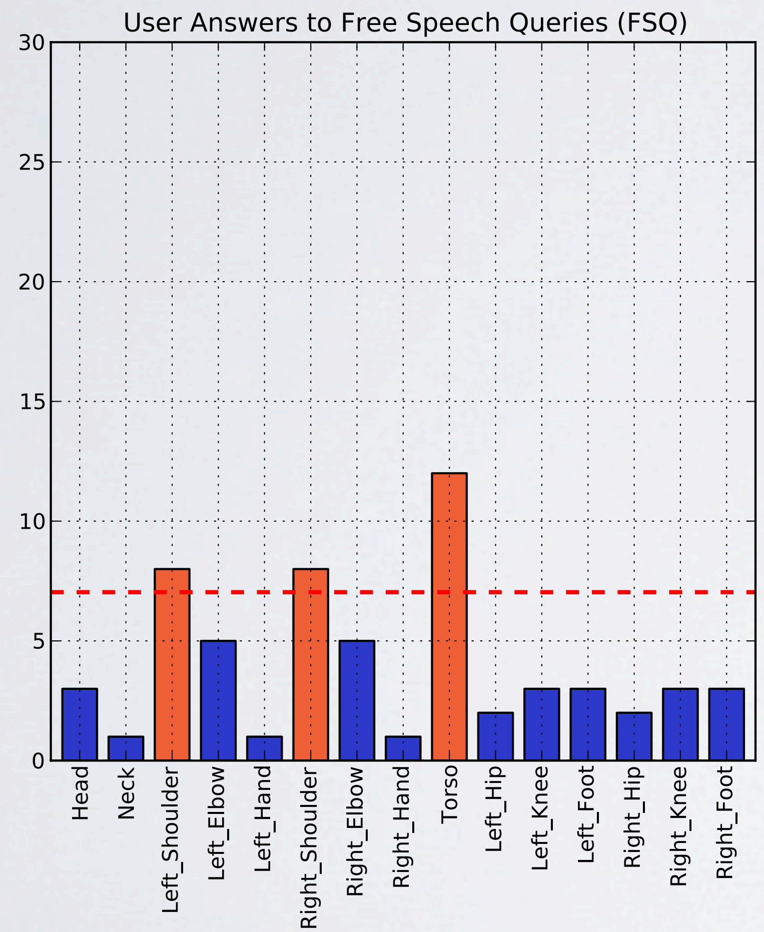
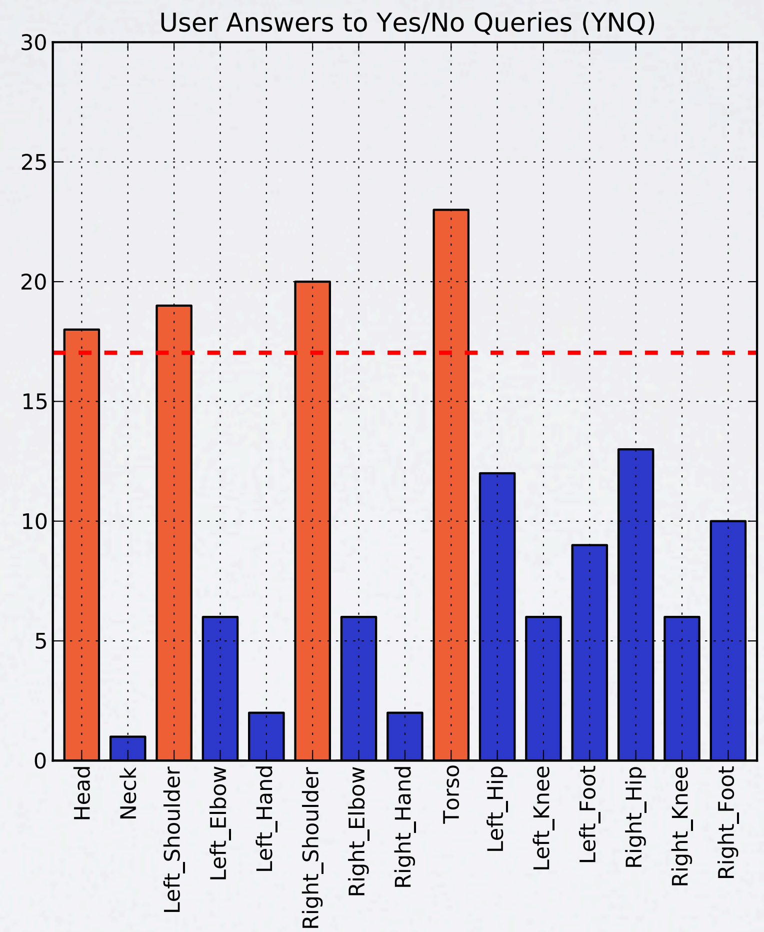
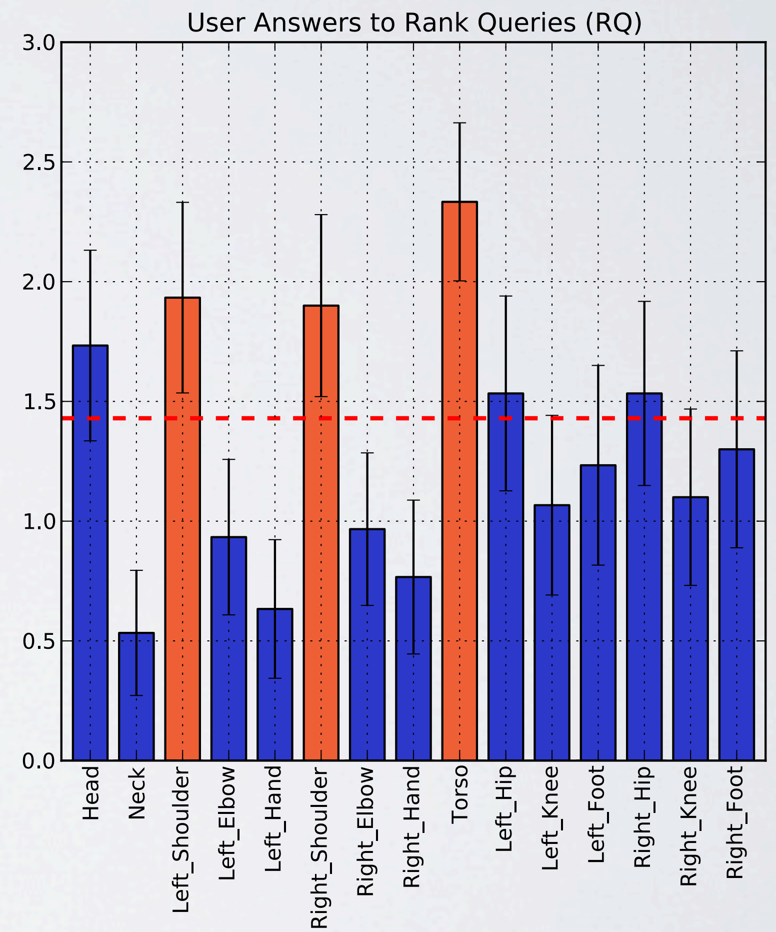


RESULTS: FEATURE FILTERS

TURNED







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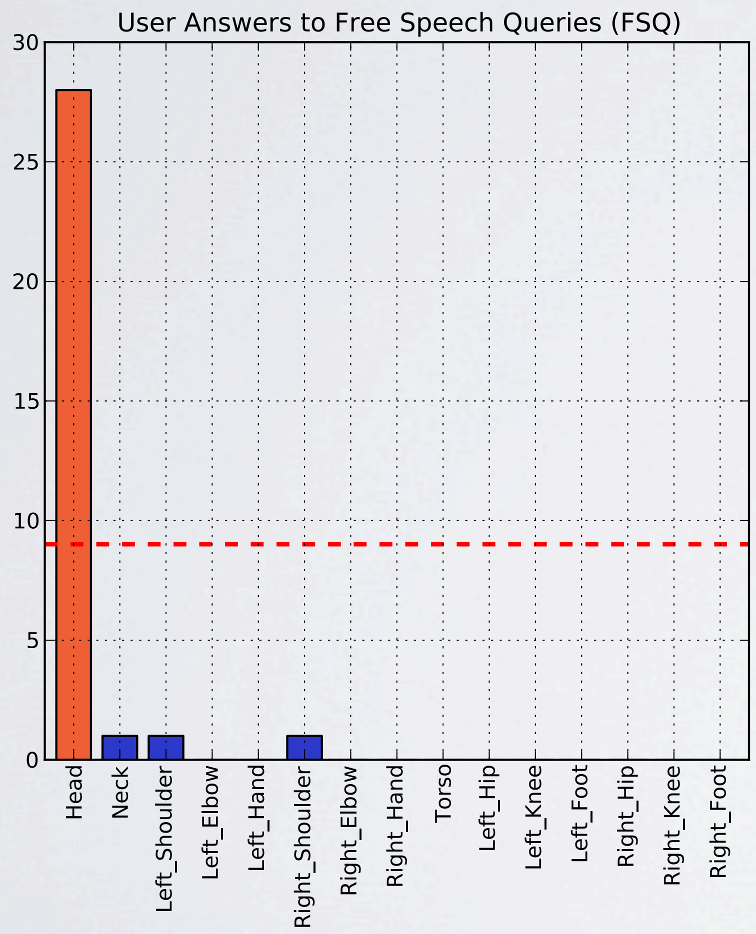
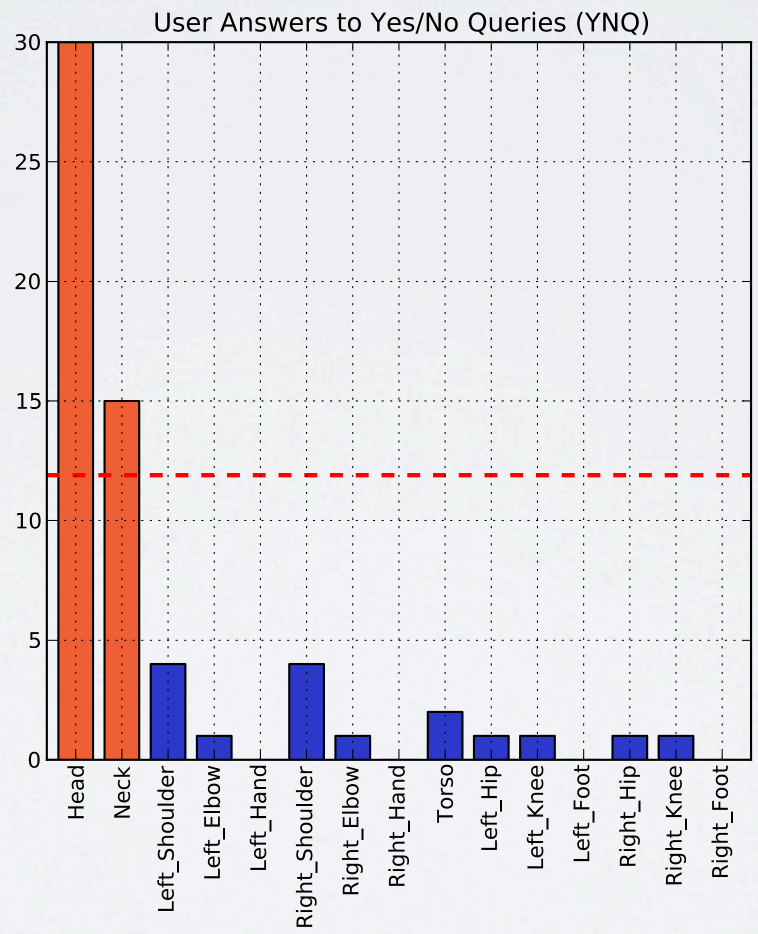
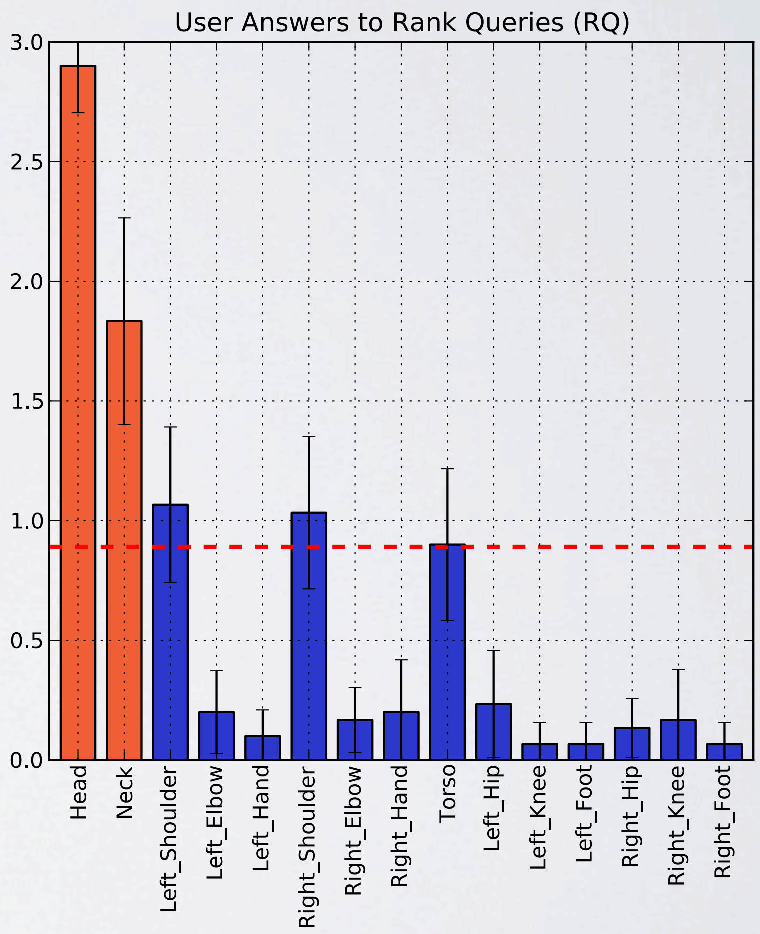
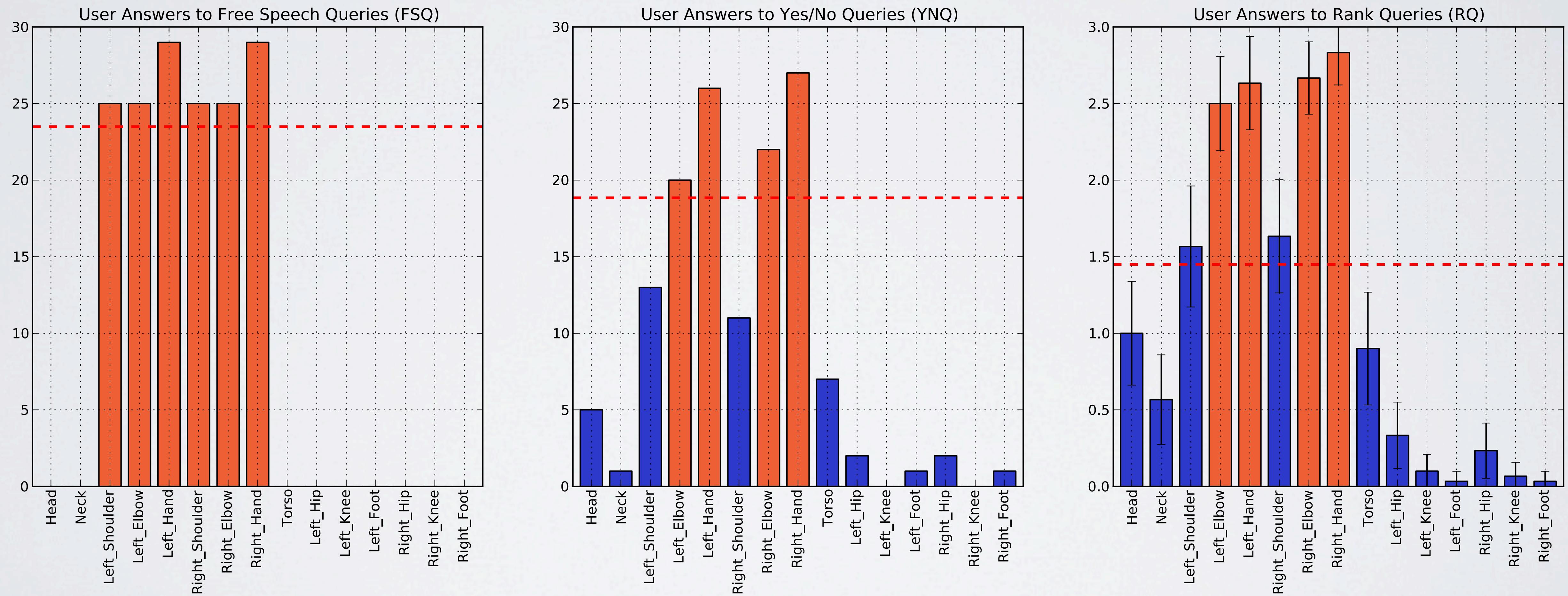






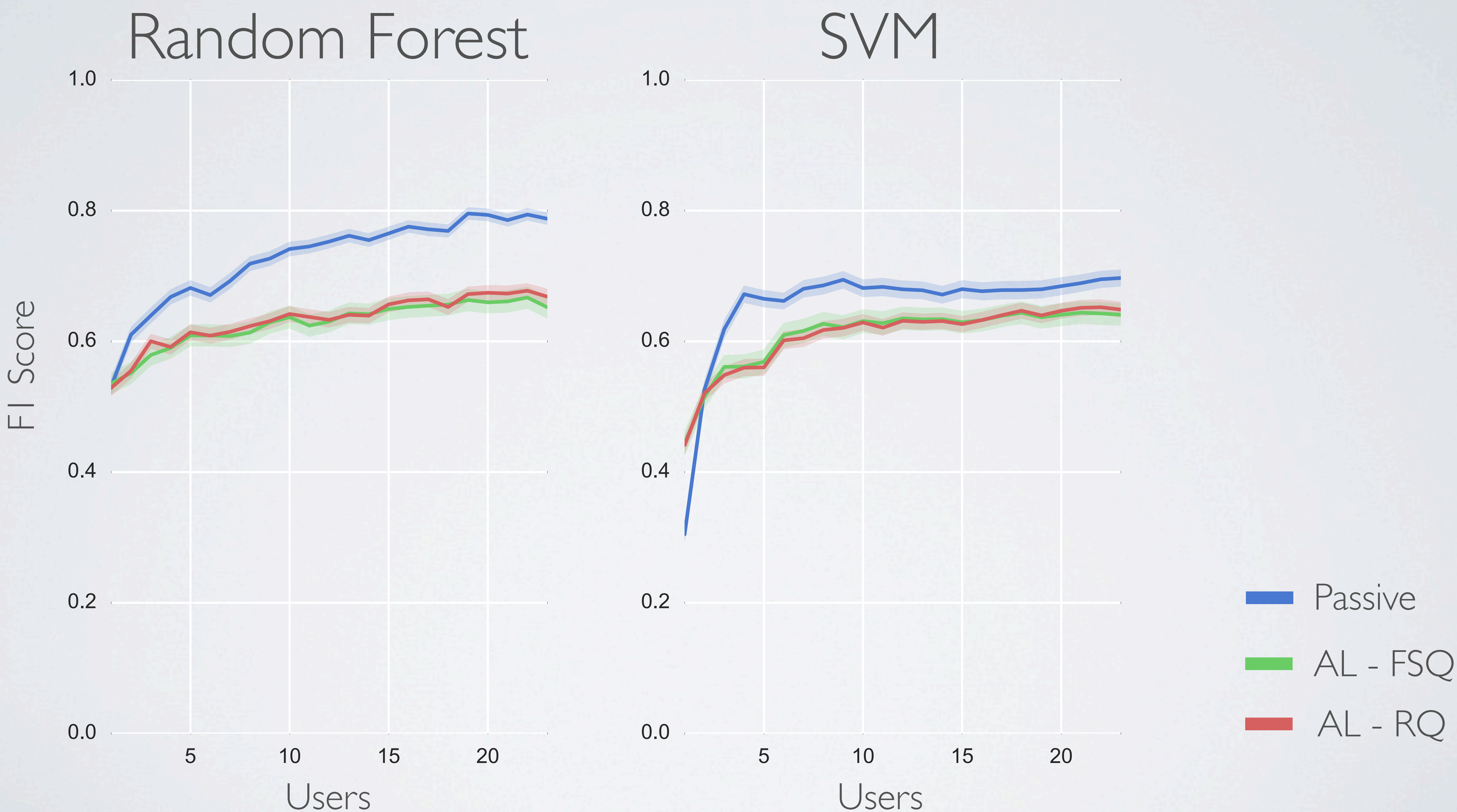
RESULTS: FEATURE FILTERS

POINTING



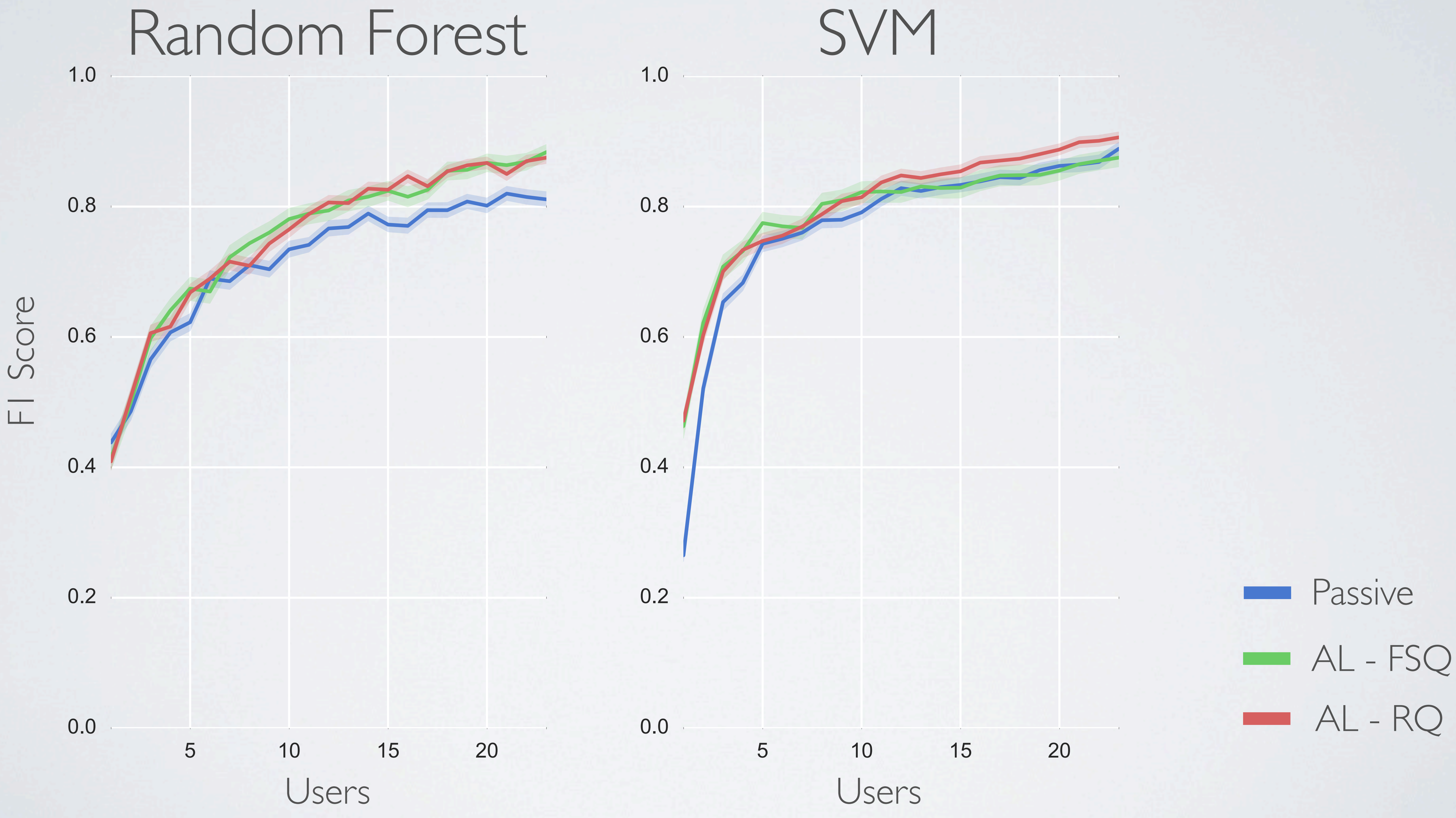
LEARNING RESULTS

LOOKING



LEARNING RESULTS

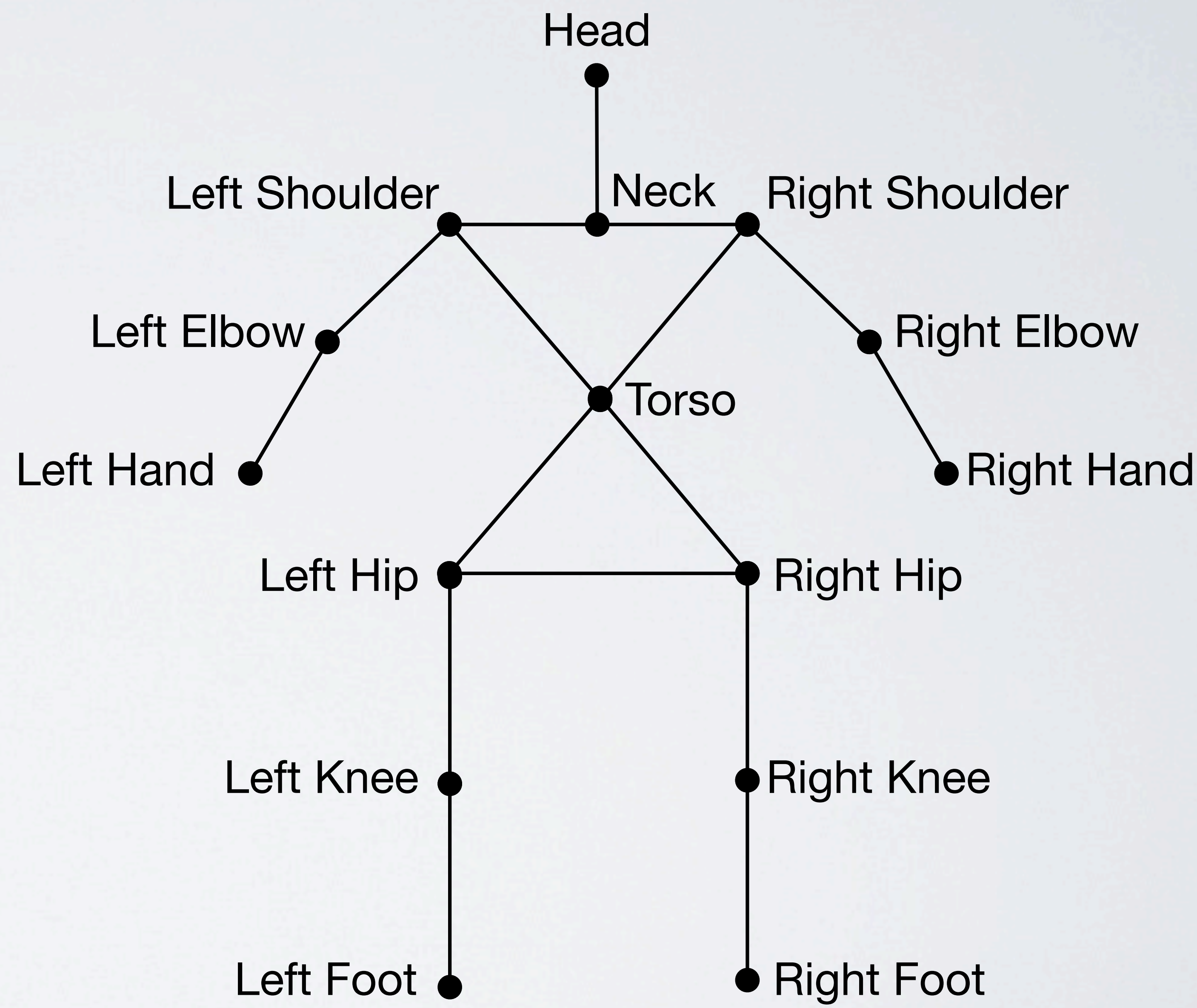
POINTING



EXTENDED FILTER

User-selected limbs

+ adjacent ones

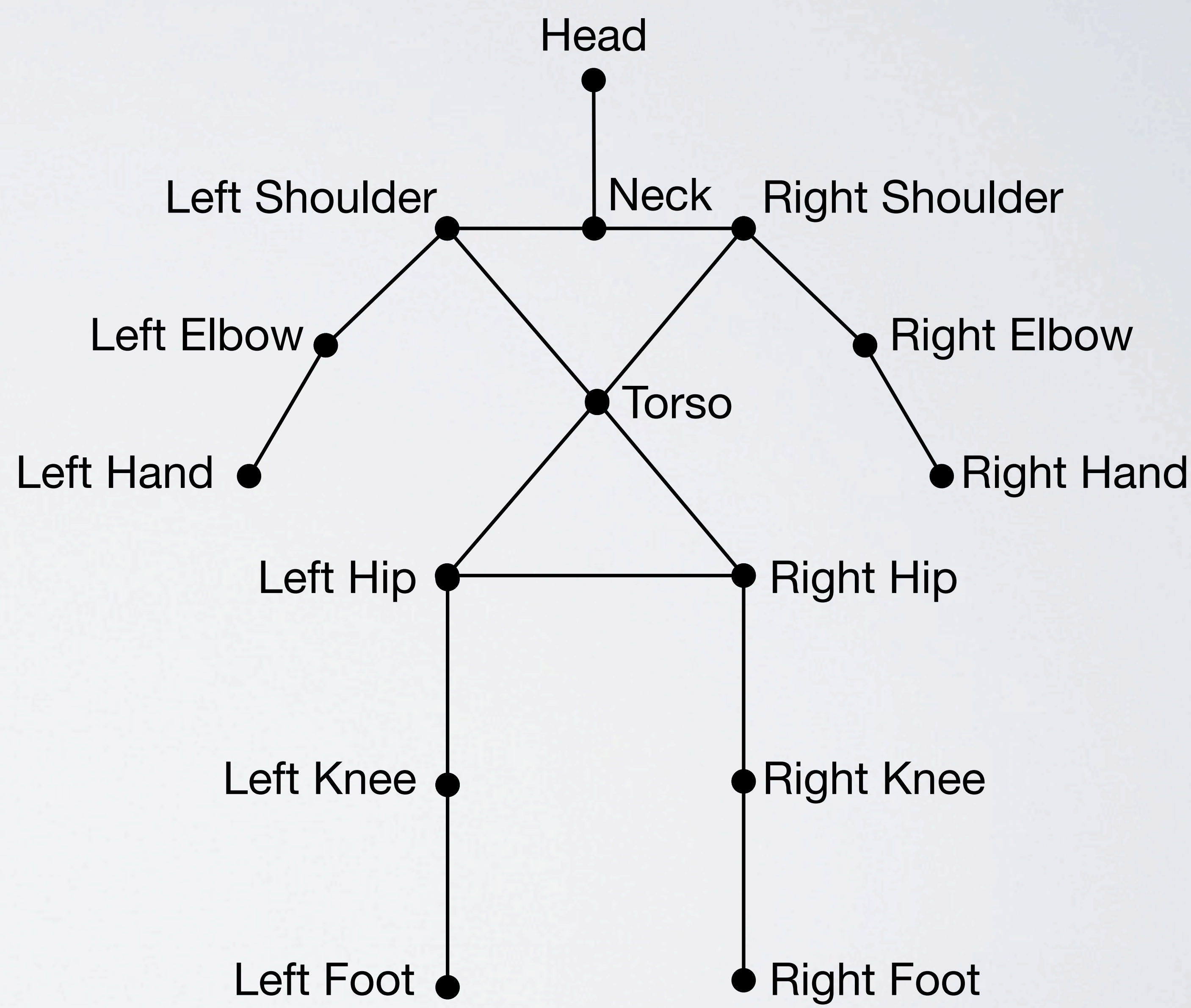


EXTENDED FILTER

User-selected limbs

+ adjacent ones

Example:



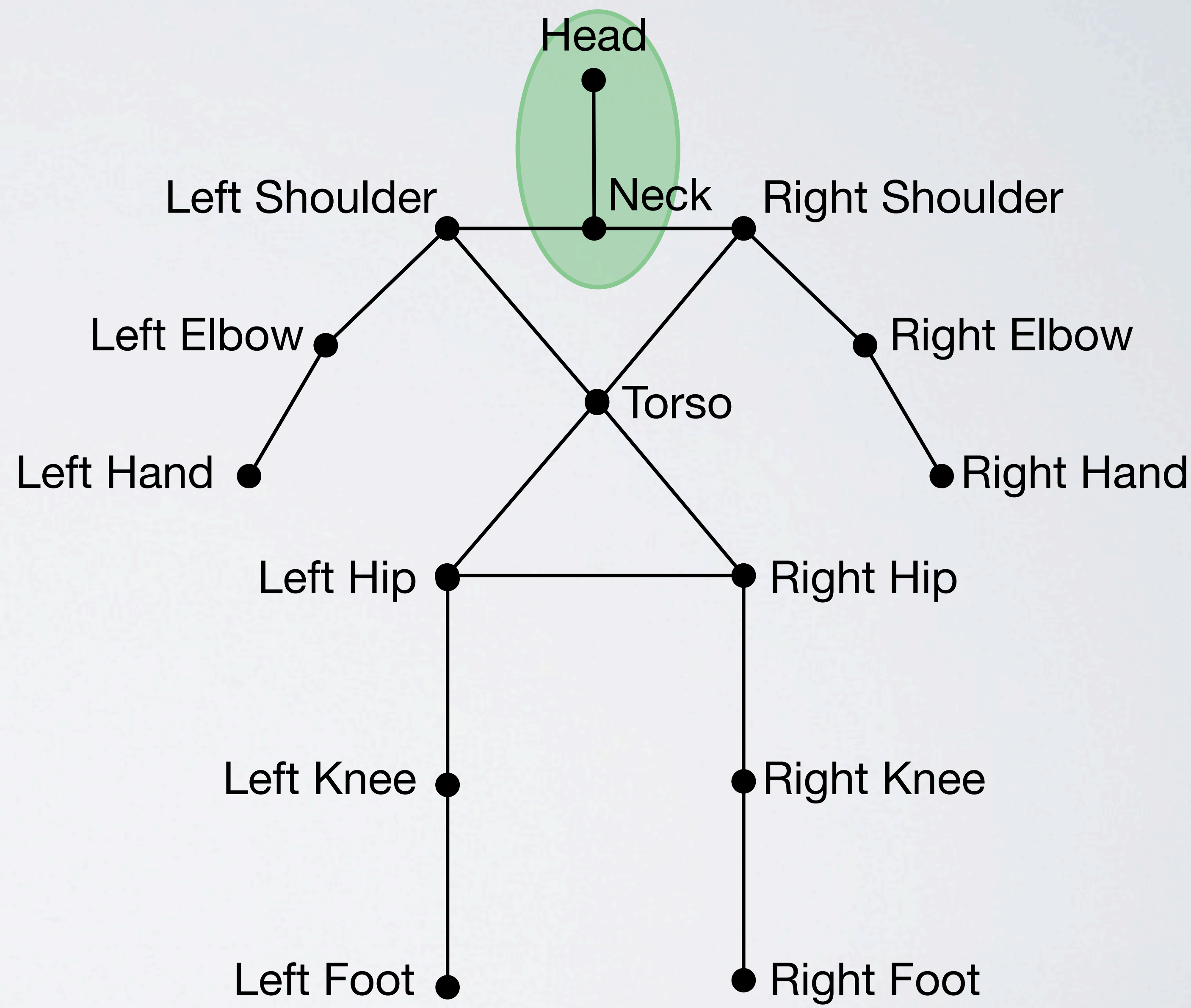
EXTENDED FILTER

User-selected limbs

+ adjacent ones

Example:

Users select: {*head*, *neck*}



EXTENDED FILTER

User-selected limbs

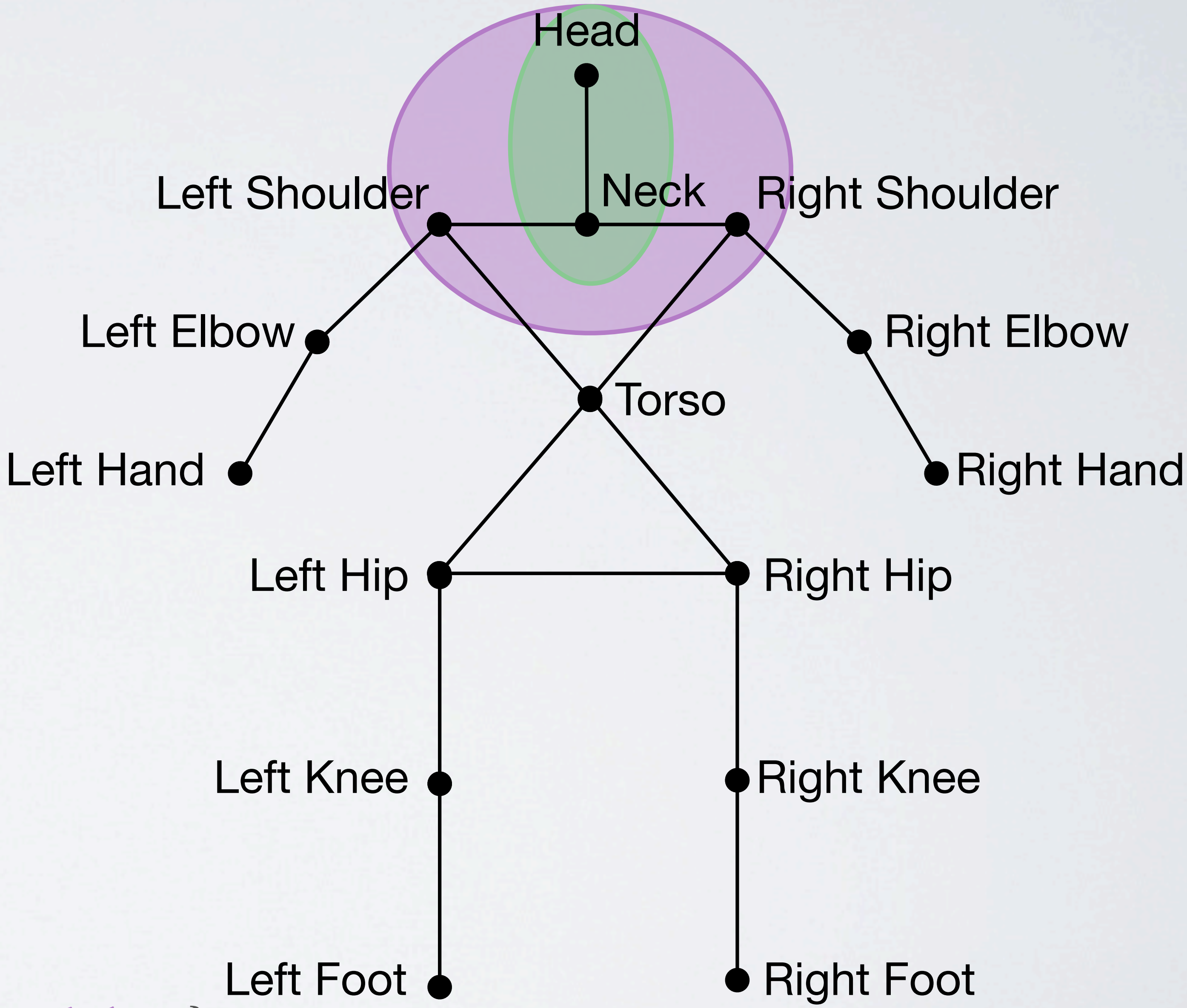
\+ adjacent ones

Example:

Users select: {*head*, *neck*}

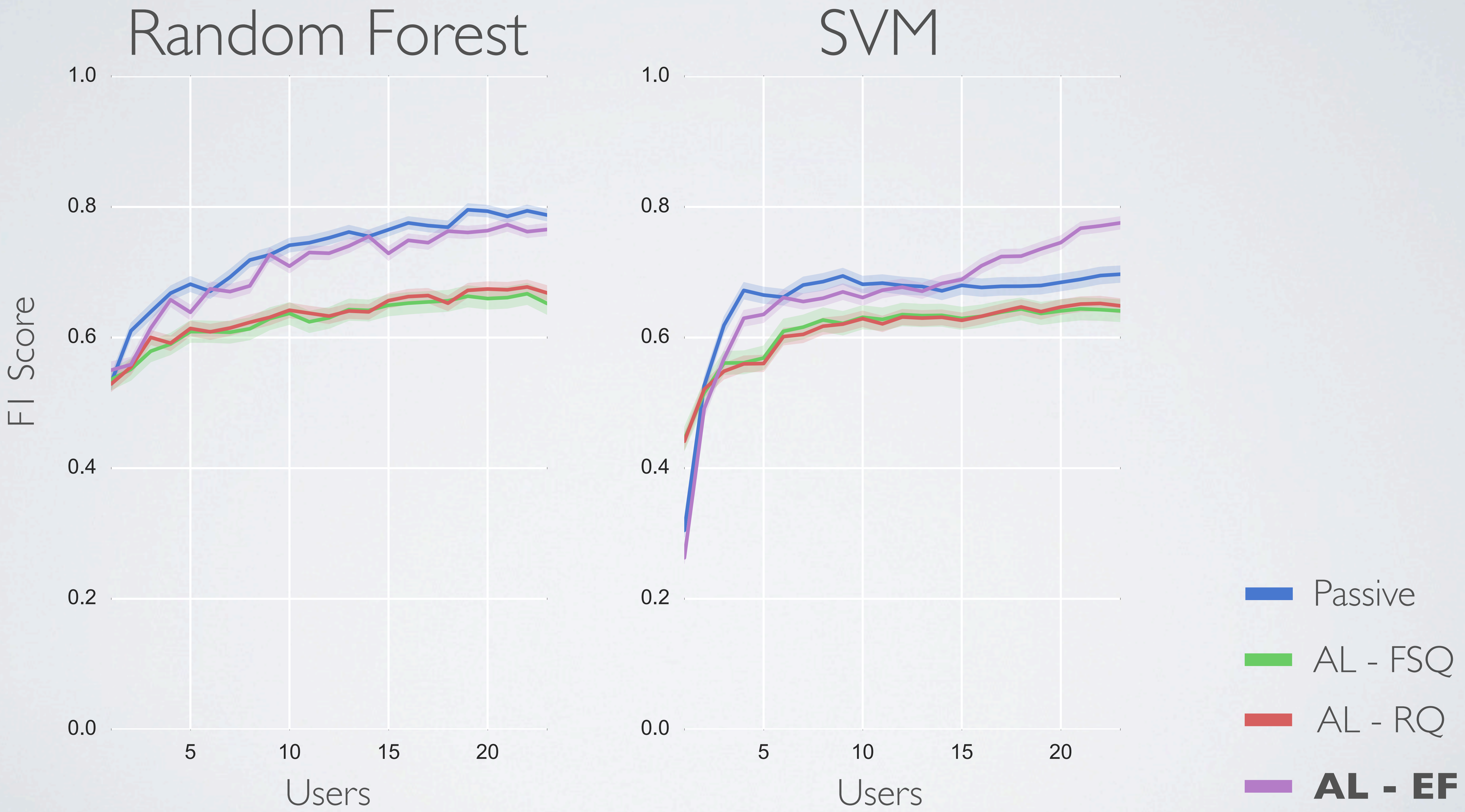
Extended Filter (EF):

{*head*, *neck*, *Lshoulder*, *Rshoulder*}



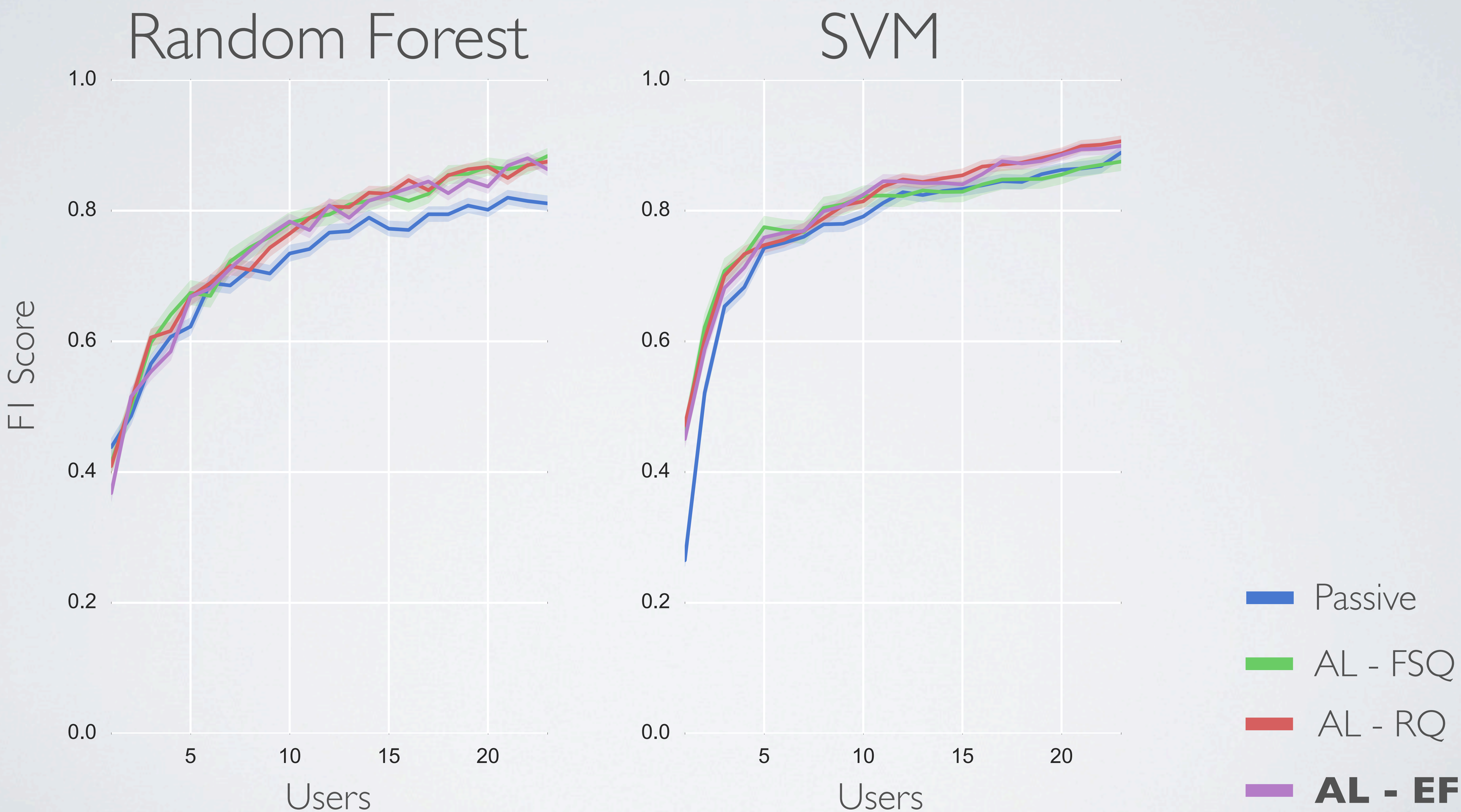
EXTENDED FILTER RESULTS

LOOKING



EXTENDED FILTER RESULTS

POINTING



CONCLUSION

Sometimes, users give innacurate answers

E.g. looking experiment

Reducing model accuracy

Extended Filter (EF) mitigates this

EF also performs well when user provides accurate answers

PUBLISHED RESULTS

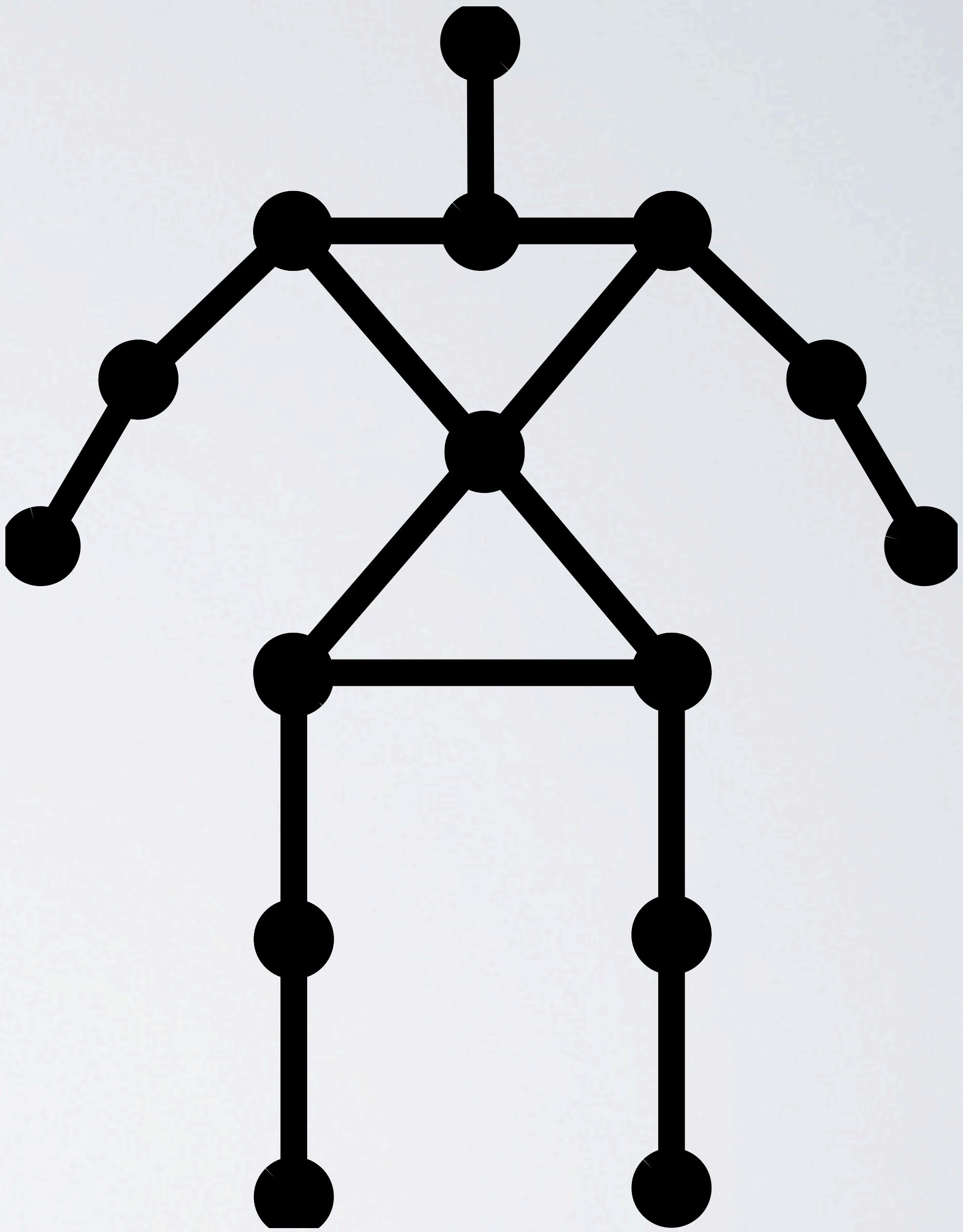
- **V. Gonzalez-Pacheco**, M. Malfaz, and M. A. Salichs, "*Asking rank queries in pose learning*," in Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction - HRI '14, 2014, pp. 164–165.

- **V. Gonzalez-Pacheco** and M. A. Salichs, "*Active Learning for Pose Recognition. Studying what and when to ask for Feature Queries*," in Proc of the 8th HRI Pioneers Workshop, 2013, pp. 3–4.

- **Victor Gonzalez-Pacheco**, María Malfaz, Álvaro Castro-González, Miguel A. Salichs. *How Much should a Social Robot trust the user feedback? Analyzing the impact of Verbal Answers in Active Learning*. Int. Journal Social Robotics. 2015 [UNDER REVIEW]

ACTIVE LEARNING

LEARNING POSES



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Part II: Interactive and Active Learning

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ACTIVE LEARNING

LEARNING OBJECTS

OBJECTIVES

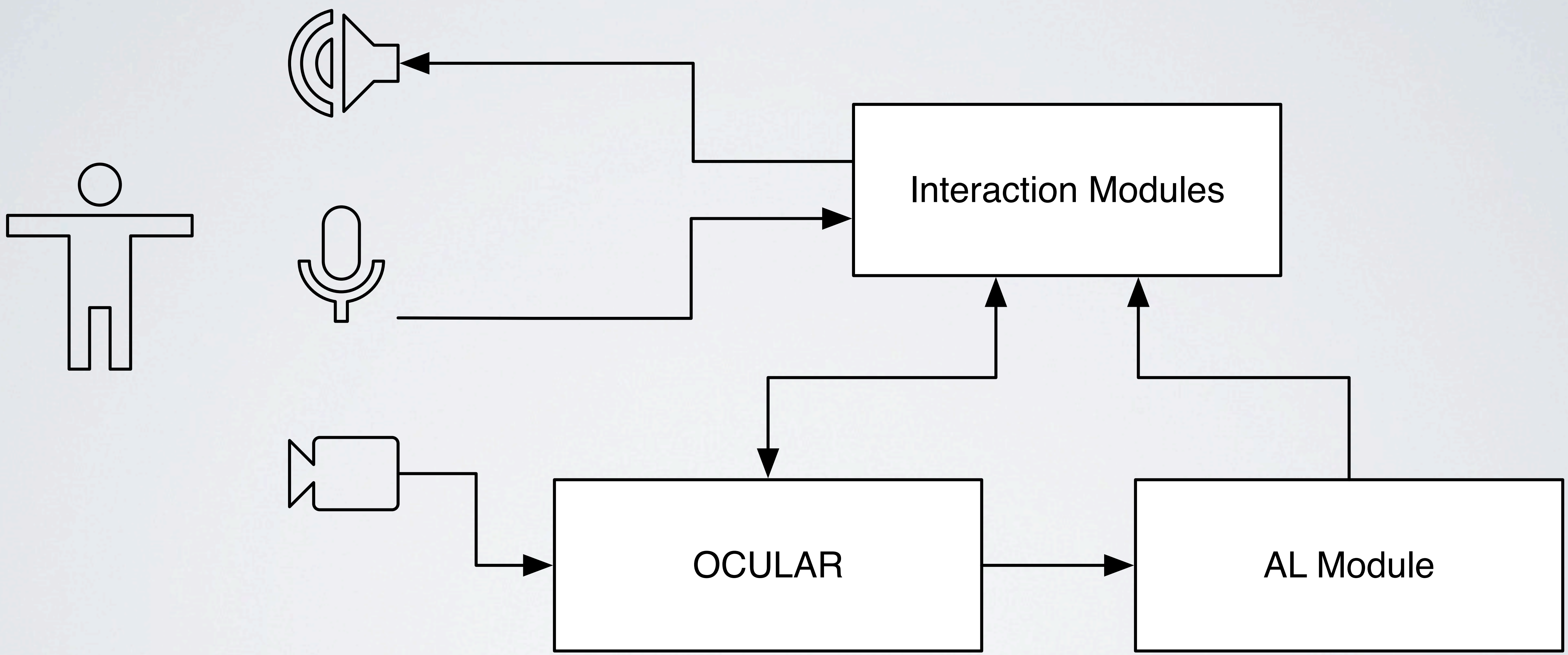
Let the robot to decide wheter it needs more examples (using Active Learning)

Increase richness of the interactions compared to previous version

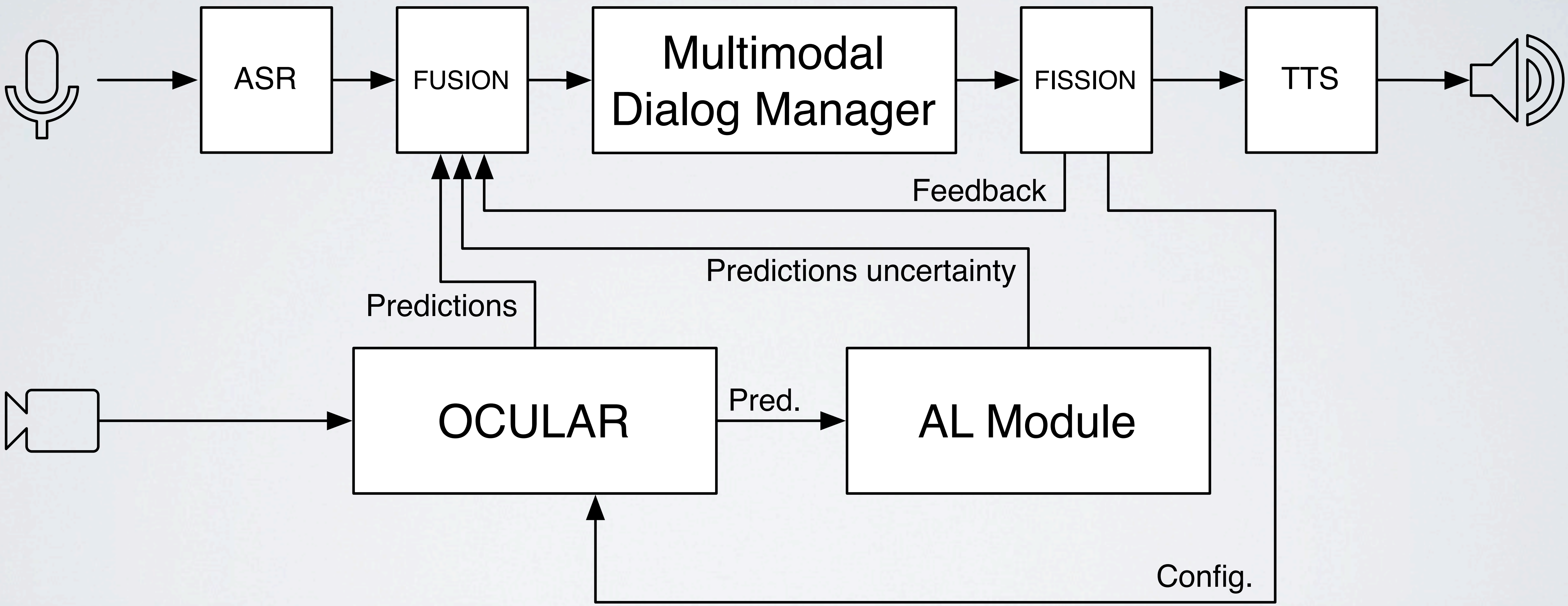
- No grammar limiting max num of objects to learn

PLATFORM
MBOT

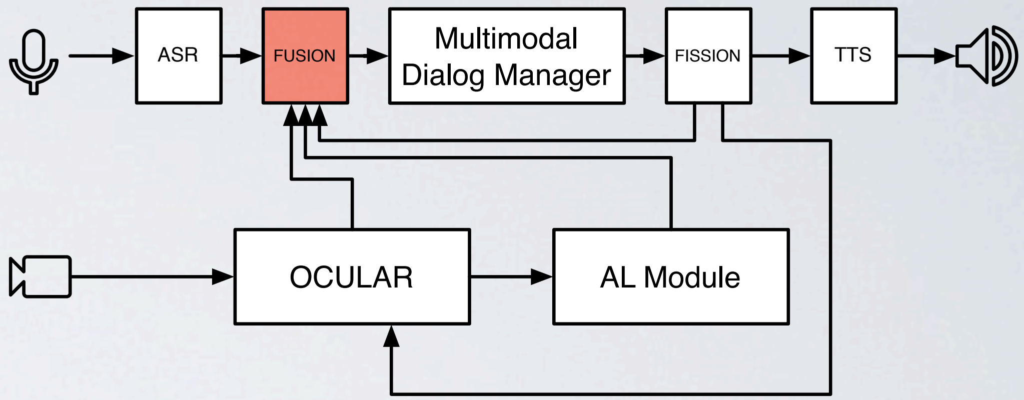
SYSTEM OVERVIEW



SYSTEM OVERVIEW



MUTIMODAL FUSION



Data aggregators (vision and language)

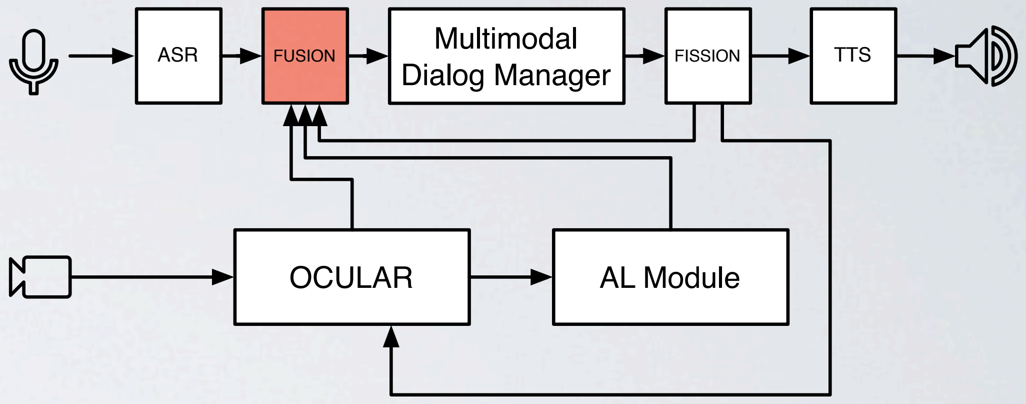
Receive Input from sensors or other modules

Produce higer level information

and send it to the Dialogue Manager

MUTIMODAL FUSION

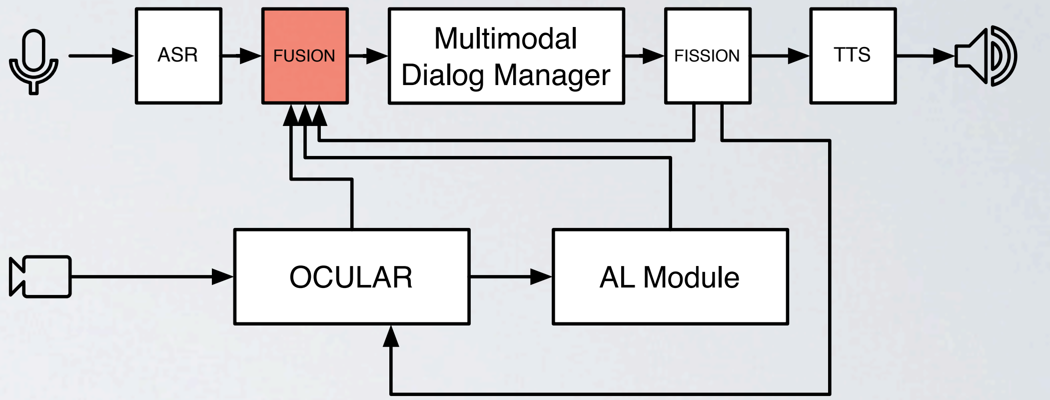
NLP MODULES



Functions:

- Stemming and Lemmatization
- Part-of-speech tagging
- Extract object names (nouns) and commands (verbs)

MUTIMODAL FUSION
NLP EXAMPLE



"Would you like to learn a new object?"

Would/**MD** you/**PRP** like/**VB** to/**TO** learn/**VB** a/**DT** new/**JJ** obect/**NN** ?/.

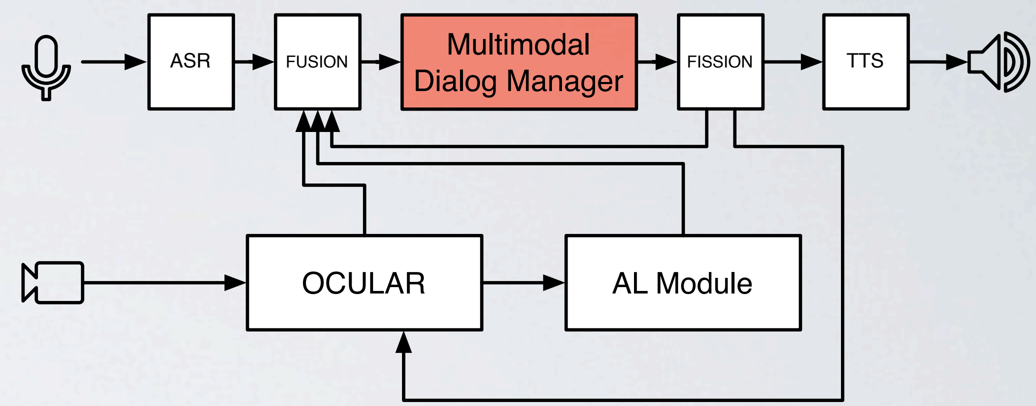
=> [command: **LEARN**]

"This is a ball"

This/**DT** be/**VB** a/**DT** ball/**NN**

=> [object:**BALL**]

DIALOGUE MANAGER



Rule-based producion system (Iwaki)

Processes high level info from Multimodal Fusion

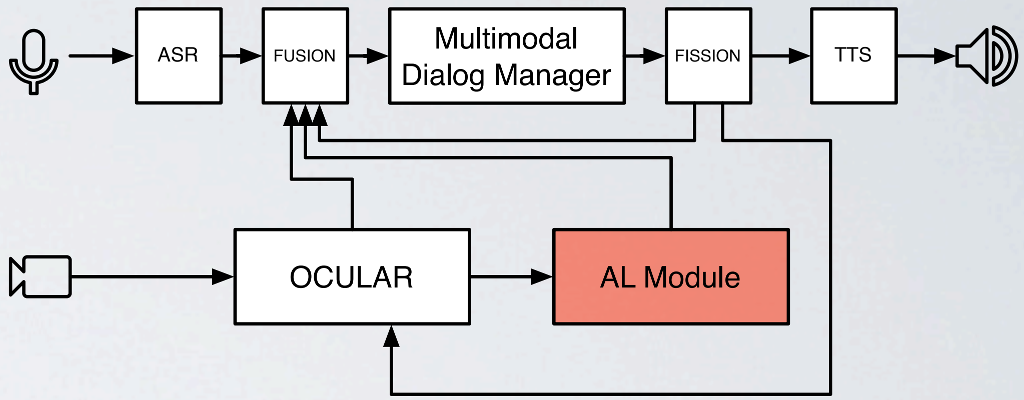
Decides what action to perform

and tells the Multimodal Fission to execute it

Dialogues are pre-coded plans written in XML files

Iwaki: https://github.com/maxipesfix/iwaki

ACTIVE LEARNING MODULE



Gets predictions from OCULAR Module

Sends uncertainty of prediction to Dialogue Manager (DM)

The decision of querying the user or not is made by the DM

ACTIVE LEARNING MODULE

UNCERTAINTY HEURISTICS

Margin (Uncertainty Sampling)

Jensen-Shannon Divergence (QBC)

Committee of 2 members: 2D matcher and 3D matcher

EXPERIMENT DESCRIPTION

4 objects

Mixed natural and artificial light

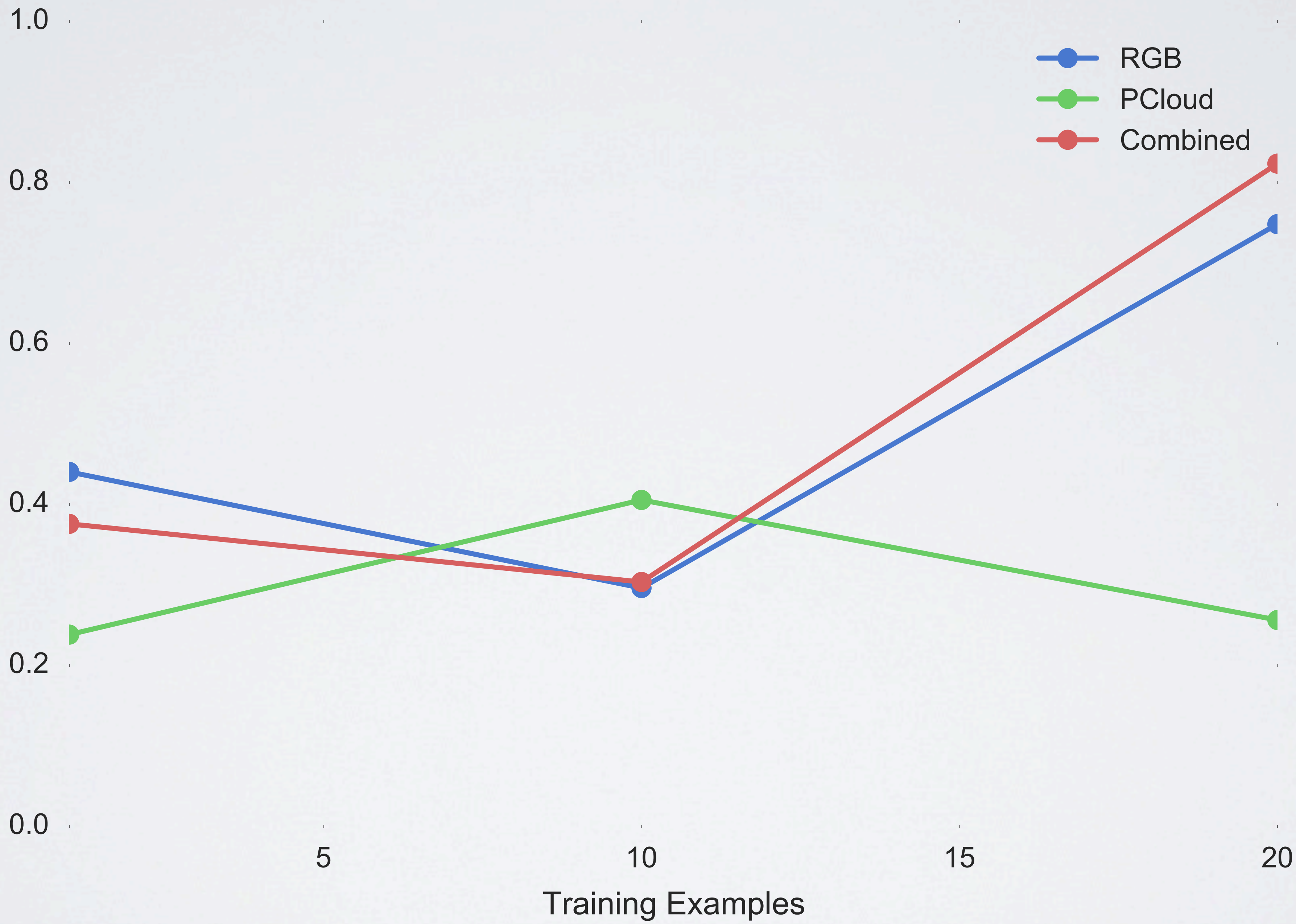
User at 1.5m~1.7m of the robot

VIDEO

VIDEO

RESULTS

F1 SCORE

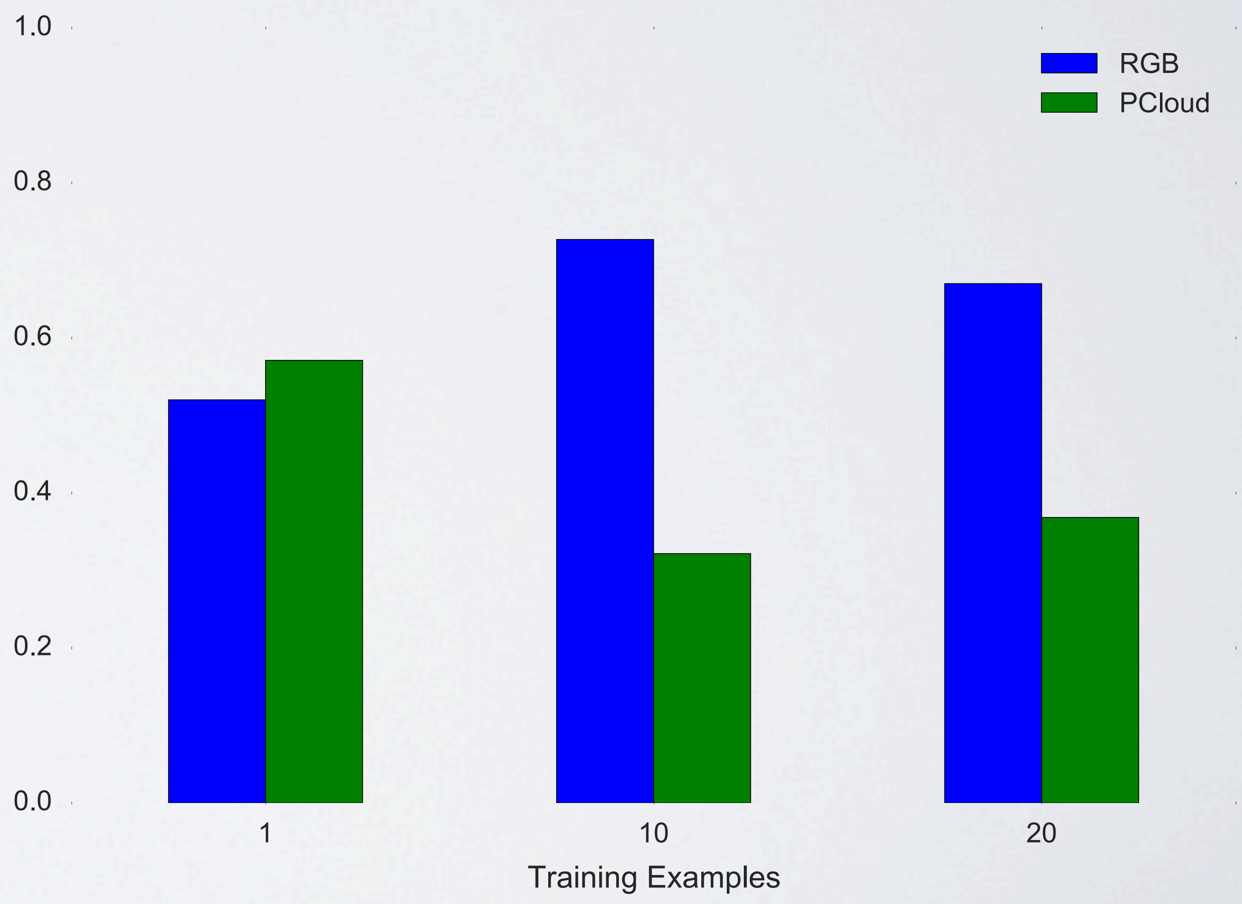


RESULTS

UNCERTAINTY LEVELS

Jensen-Shannon Divergence

Margin



CONCLUSION

Robot can learn after training session has ended

Poor performance of Point Cloud matcher

High divergence between matchers

Very verbose when querying

- Use different strategy for querying

ACTIVE LEARNING

LEARNING OBJECTS

Introduction

Part I: Interactive Learning

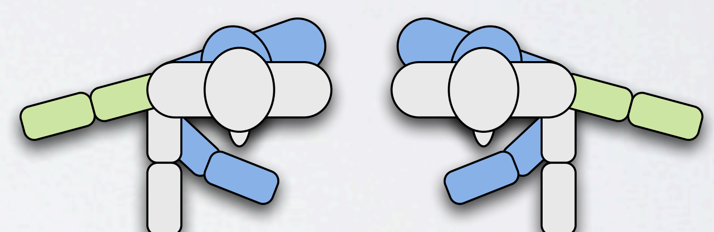
Poses

Objects

Part II: Interactive and Active Learning

Poses

Objects

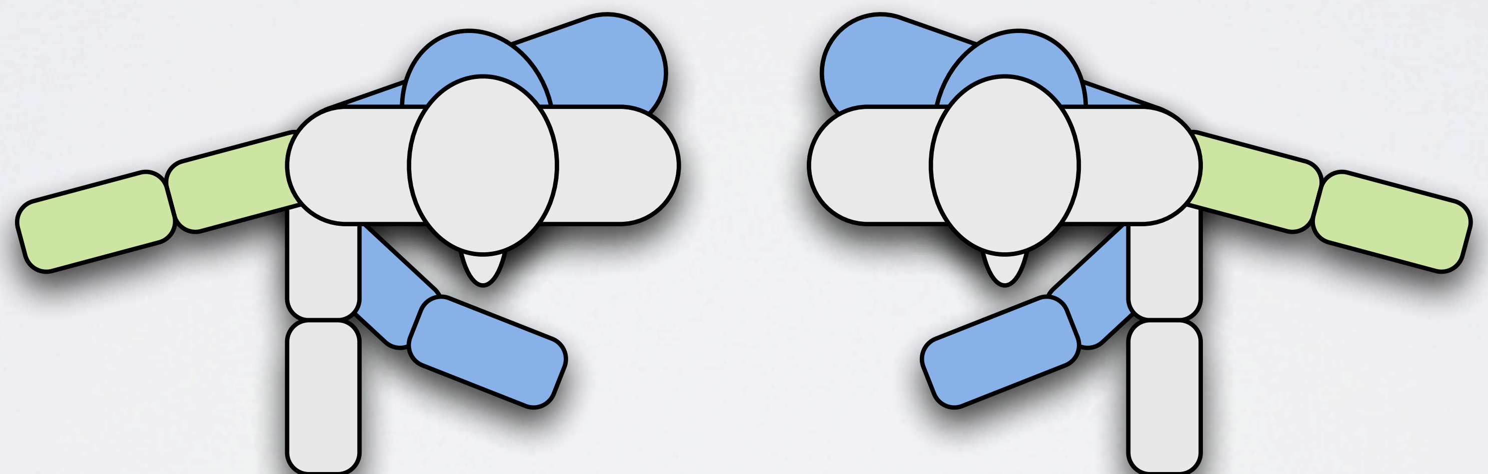


Novelties

Conclusions

INTERACTIVE AND ACTIVE LEARNING

NOVELTY DETECTION



MOTIVATION

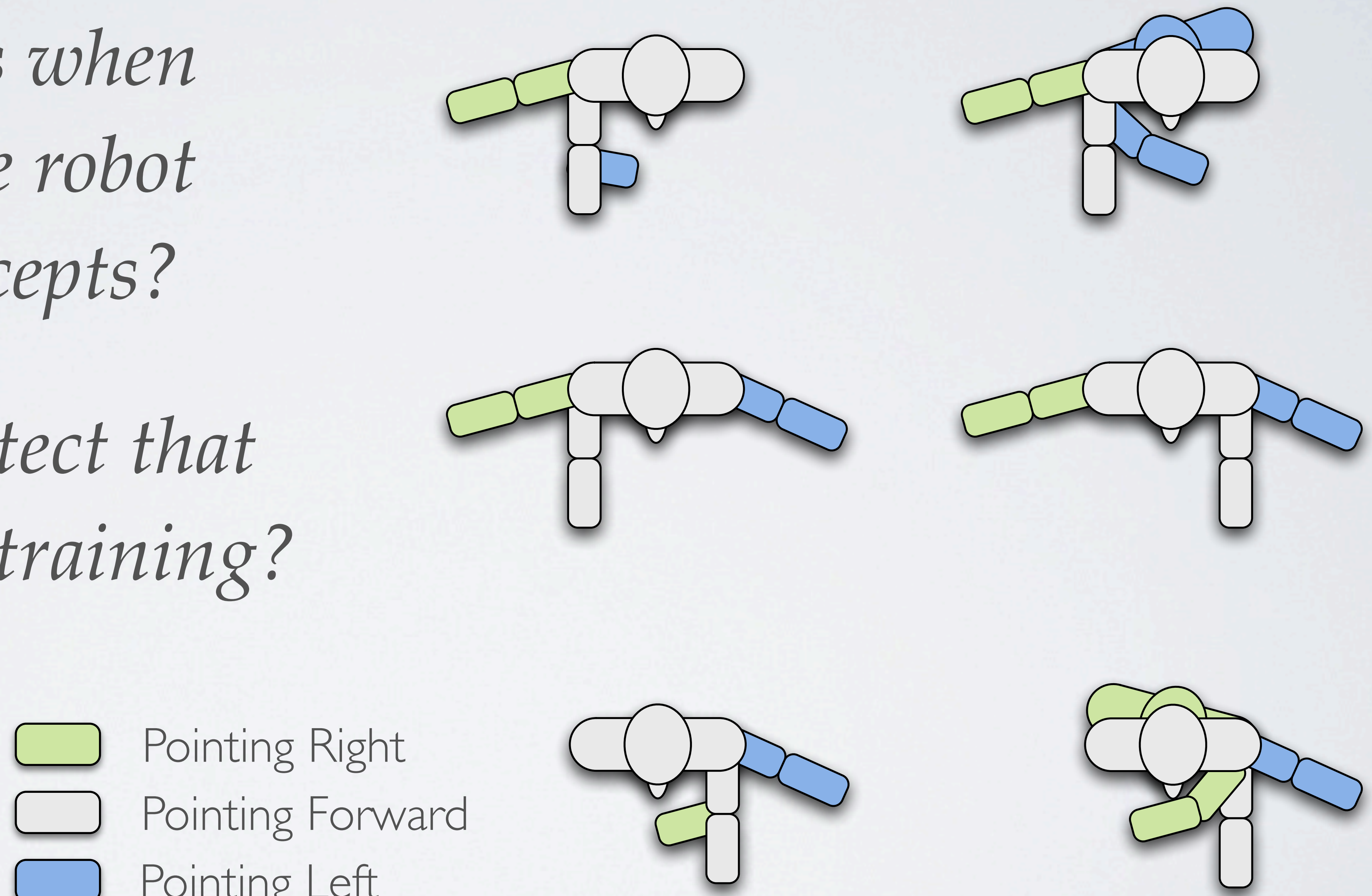
What happens when you expose the robot with new concepts?

Is it able to detect that it needs more training?

MOTIVATION

What happens when you expose the robot with new concepts?

Is it able to detect that it needs more training?



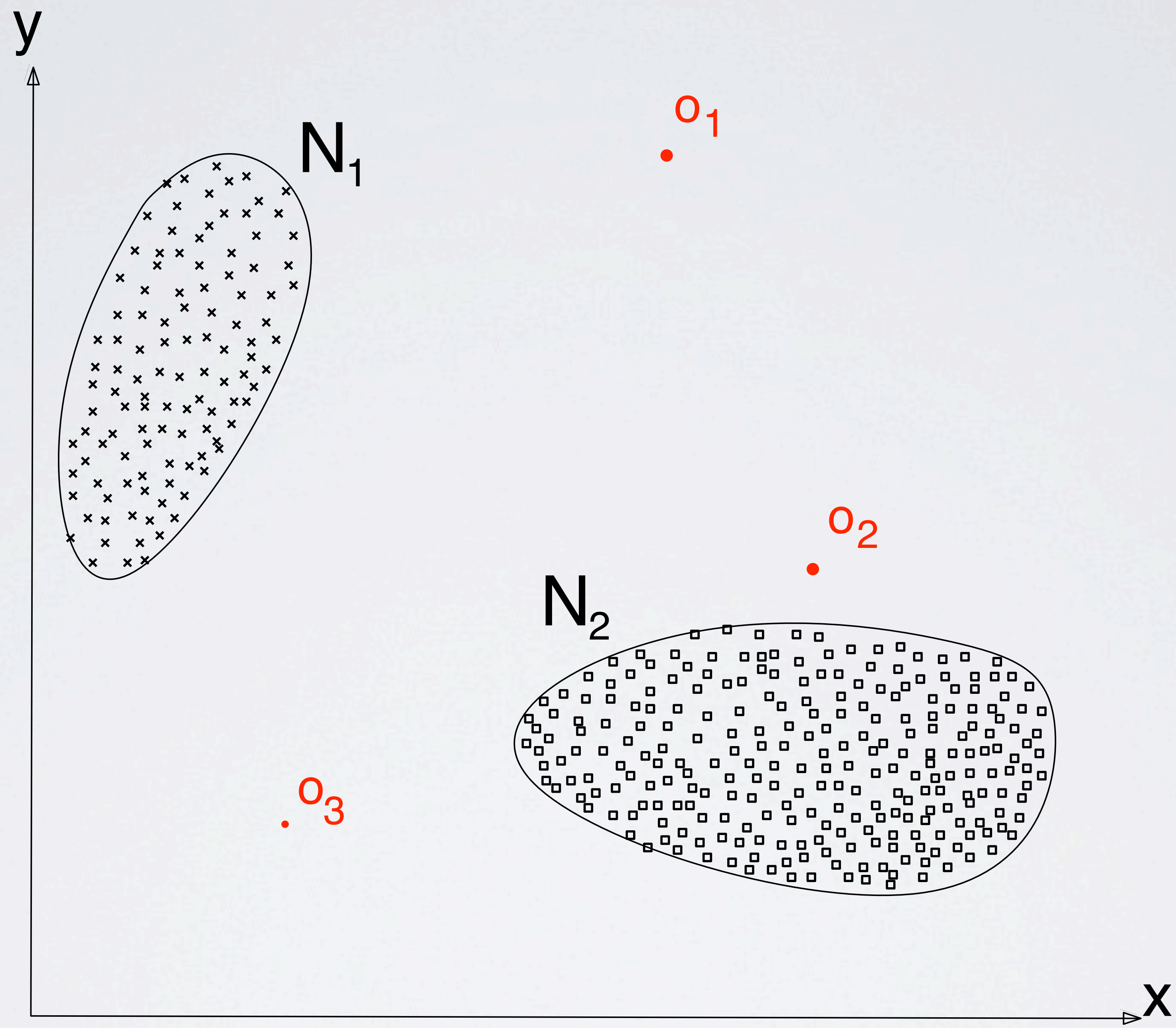
OBJECTIVES

Learn from novel data

Filter non-interesting **noise**

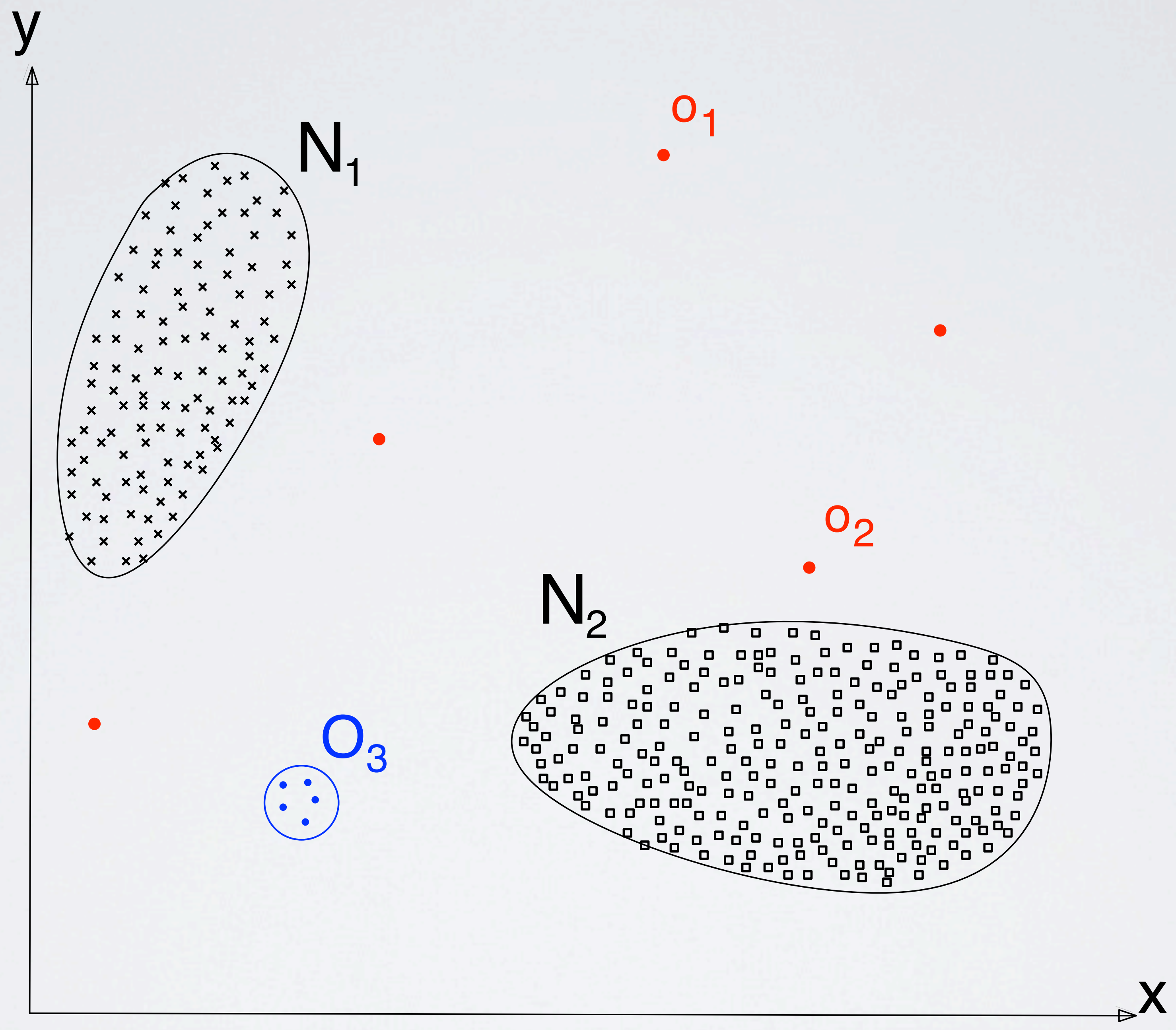
Distinguish between **known** and **strange**

NOVELTY DETECTION



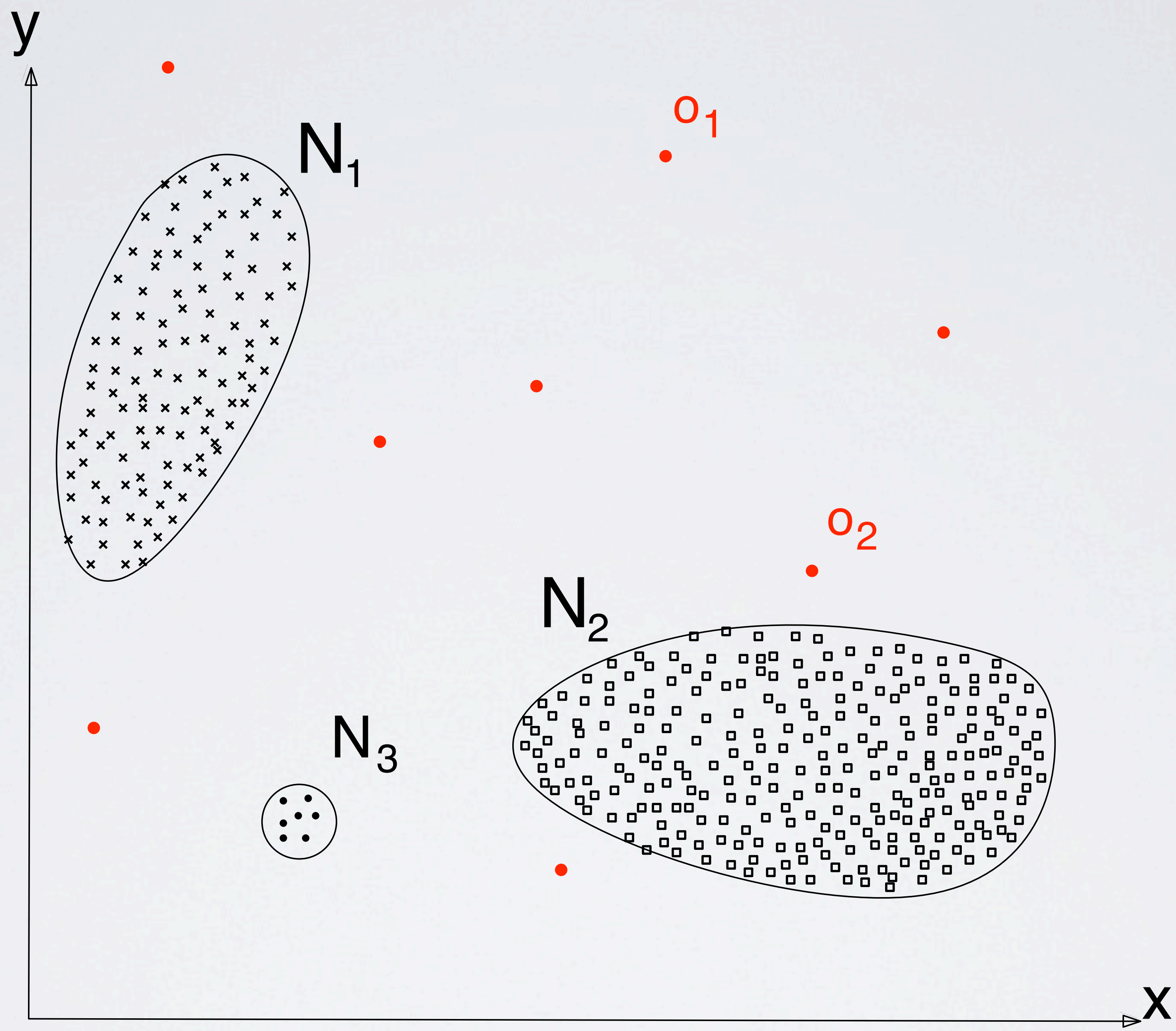
Novel: ***new***, ***interesting*** *and* ***strange***

NOVELTY DETECTION



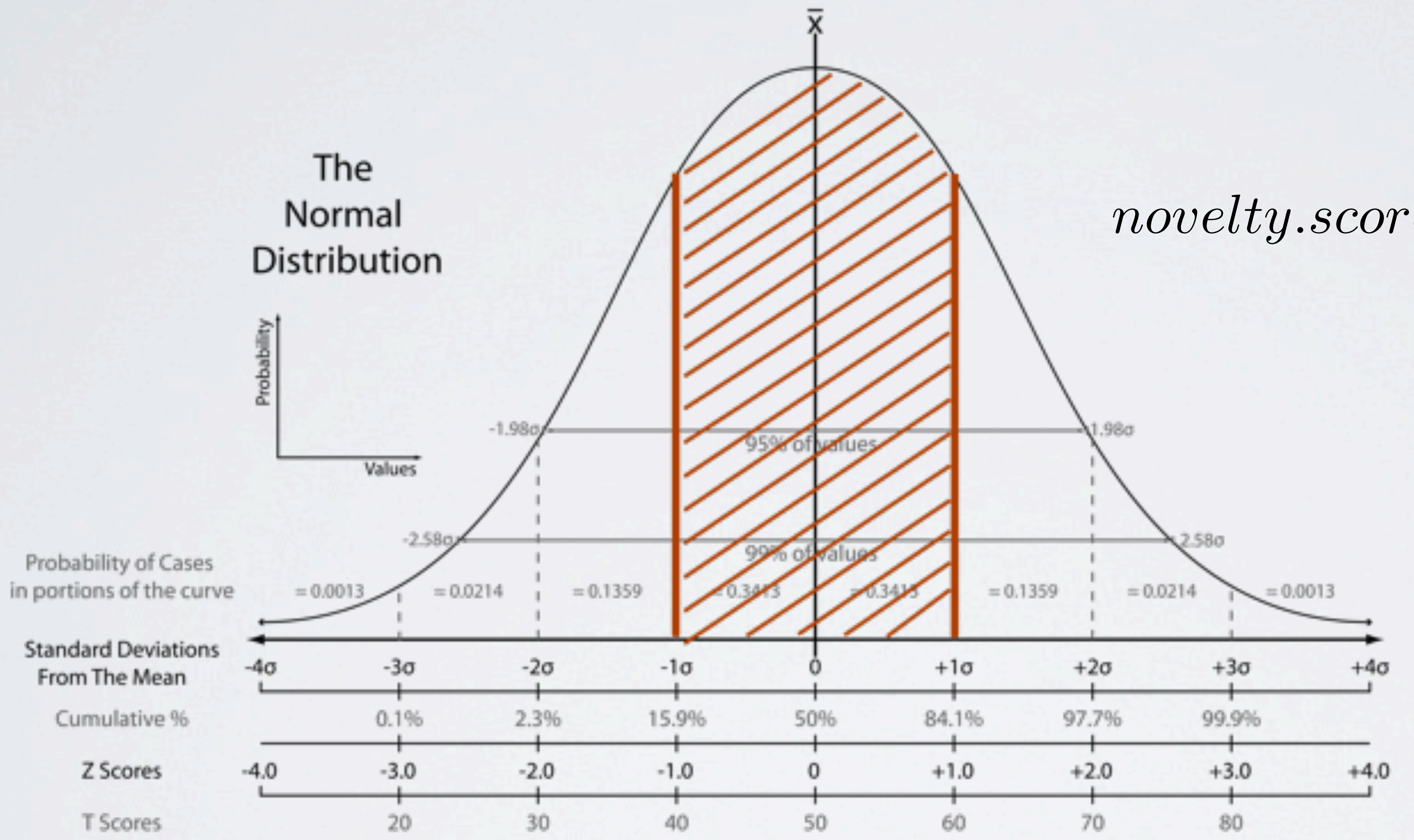
Novel: ***new***, ***interesting*** *and* ***strange***

NOVELTY DETECTION



Novel: ***new***, ***interesting*** *and* ***strange***

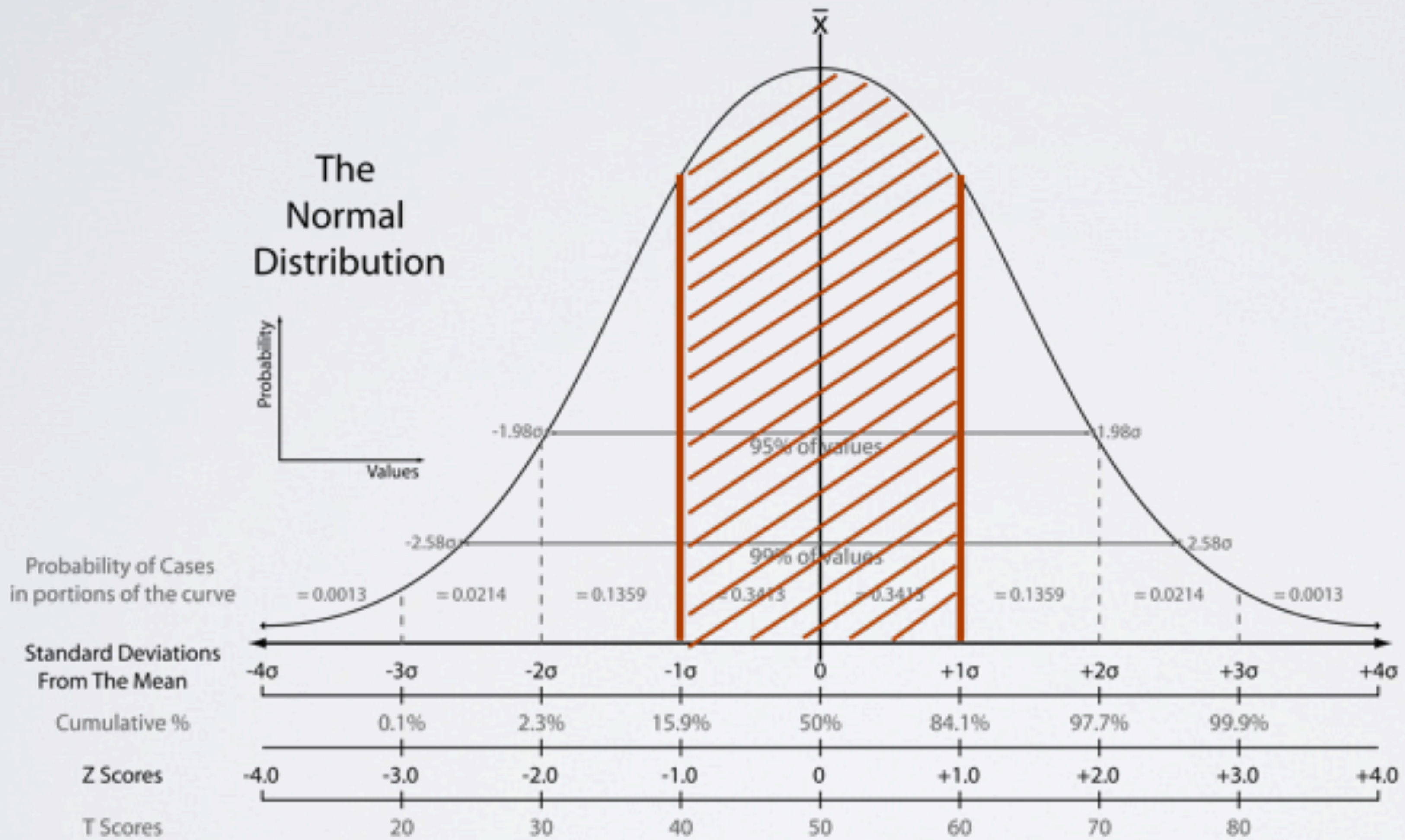
Novelty Score



$$novelty.score(o_1) = abs(\frac{z(o_1) - \mu}{\sigma})$$

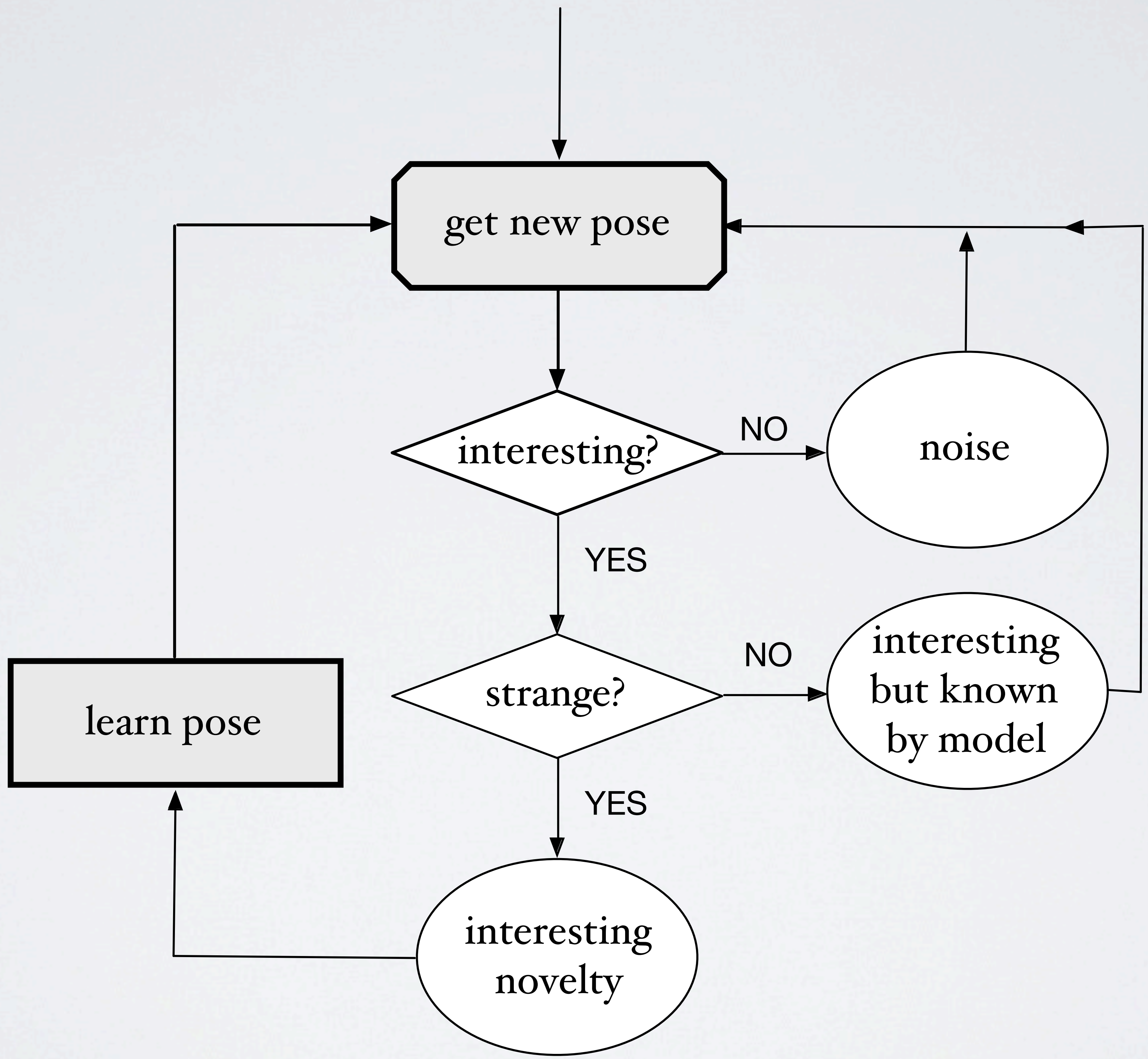
Extreme Value Theorem (EVT)

K curiosity factor

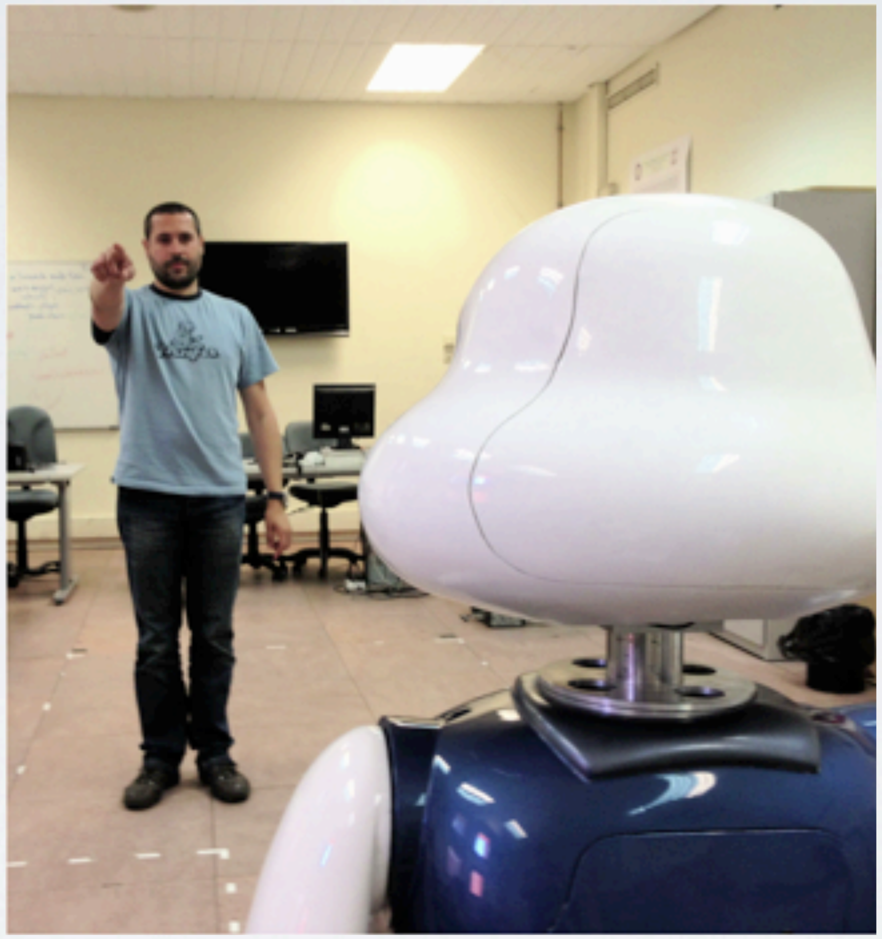


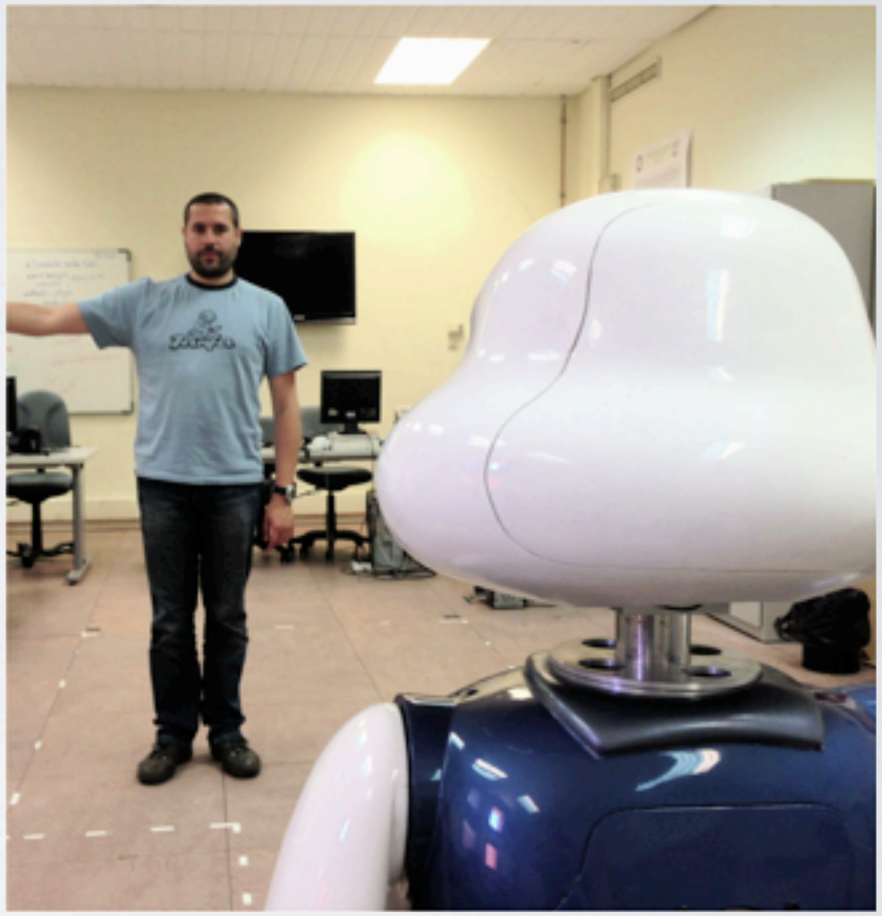
$$K \geq abs(\frac{z(o_1) - \mu}{\sigma}) \qquad 1 \geq abs(\frac{z(o_1) - \mu}{K \times \sigma})$$

SYSTEM DIAGRAM



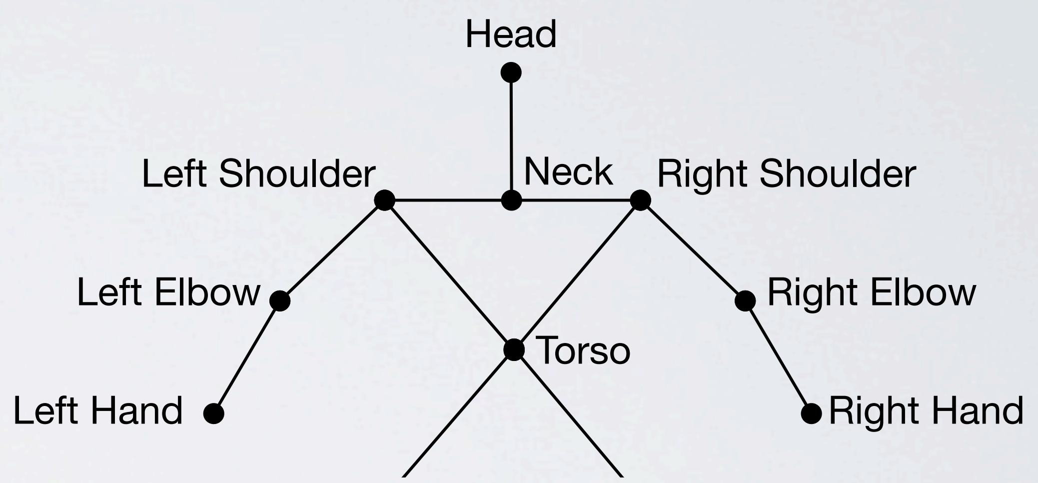
EXPERIMENTS



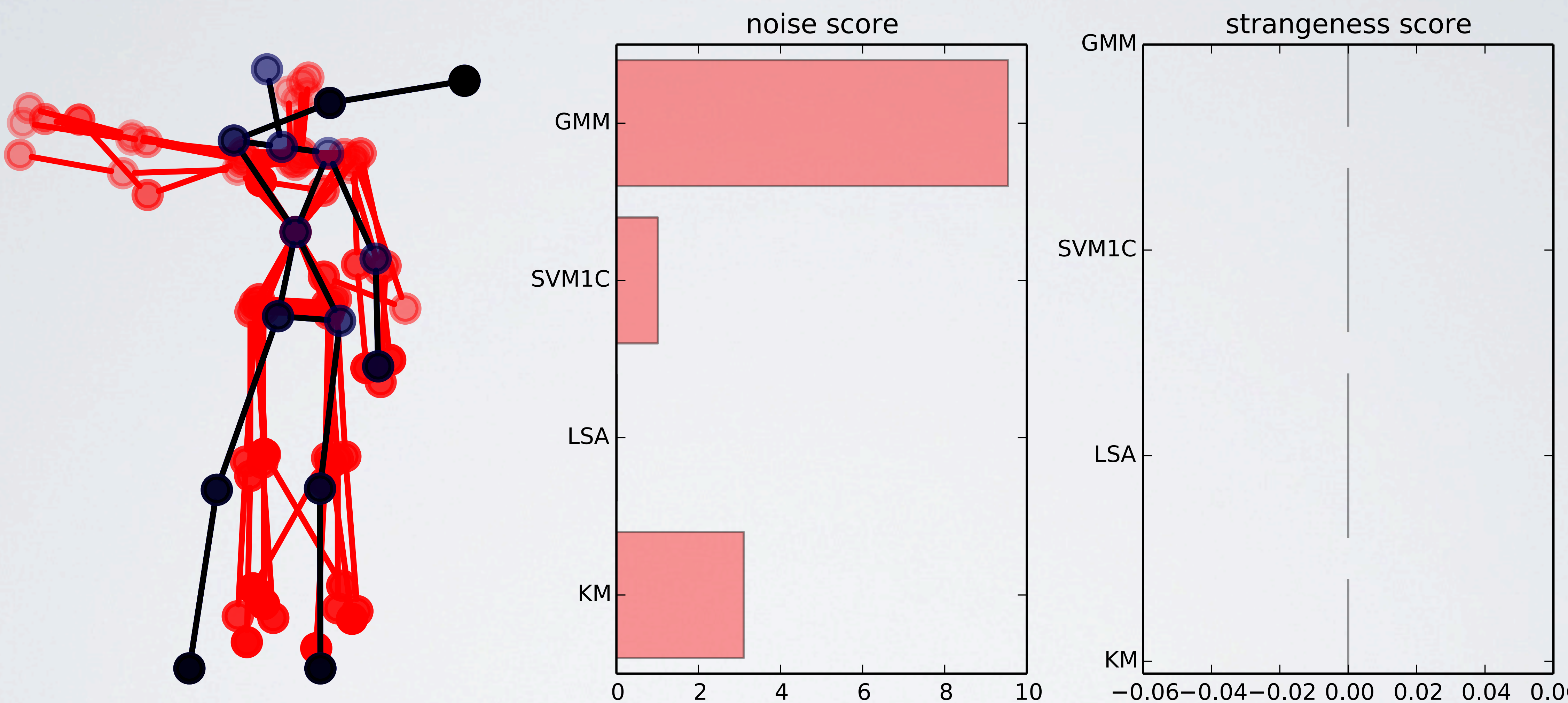


FILTERED JOINTS

9 Joints
7 Parameters per joint:
$(x, y, z, q_x, q_y, q_z, q_w)$



LET'S SEE AN EXAMPLE

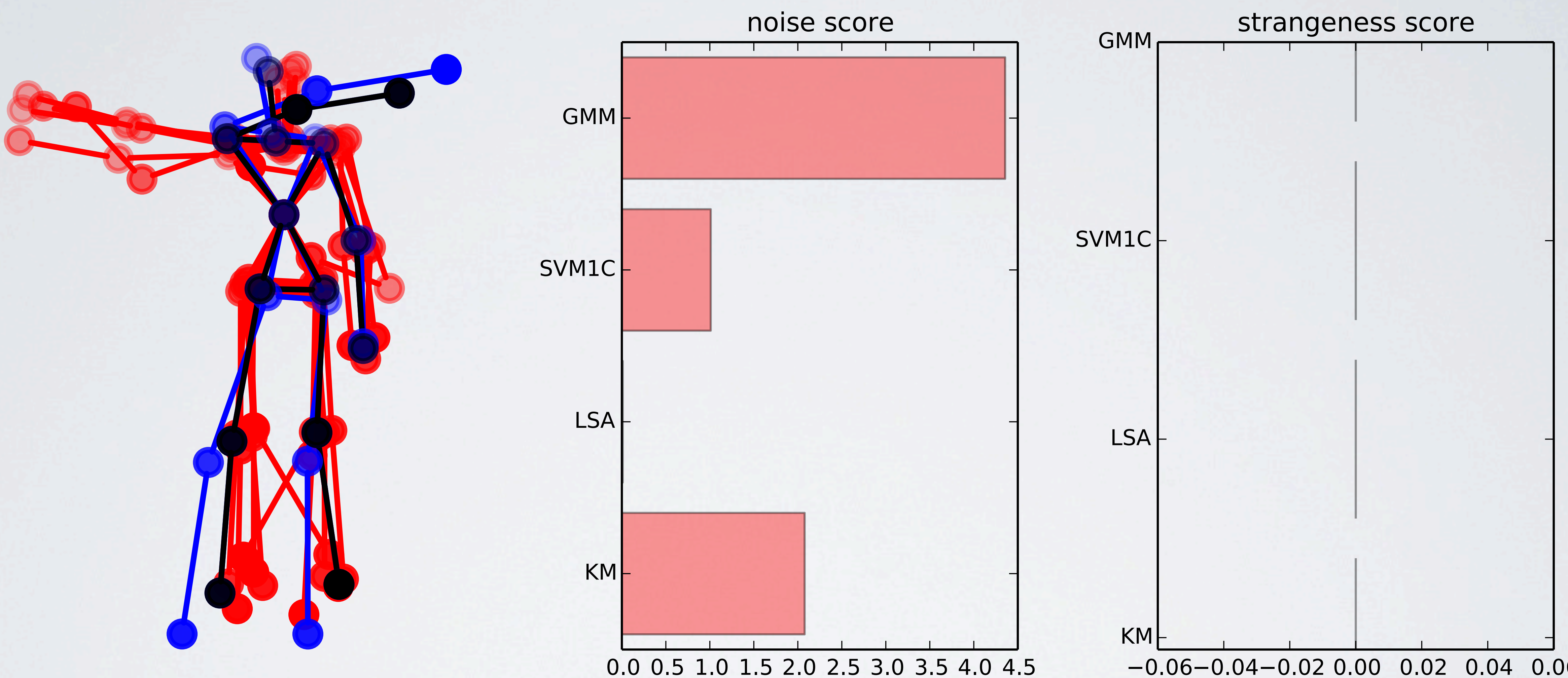


Observed poses (previous sessions)

Current observed pose

Observed poses (during session)

LET'S SEE AN EXAMPLE

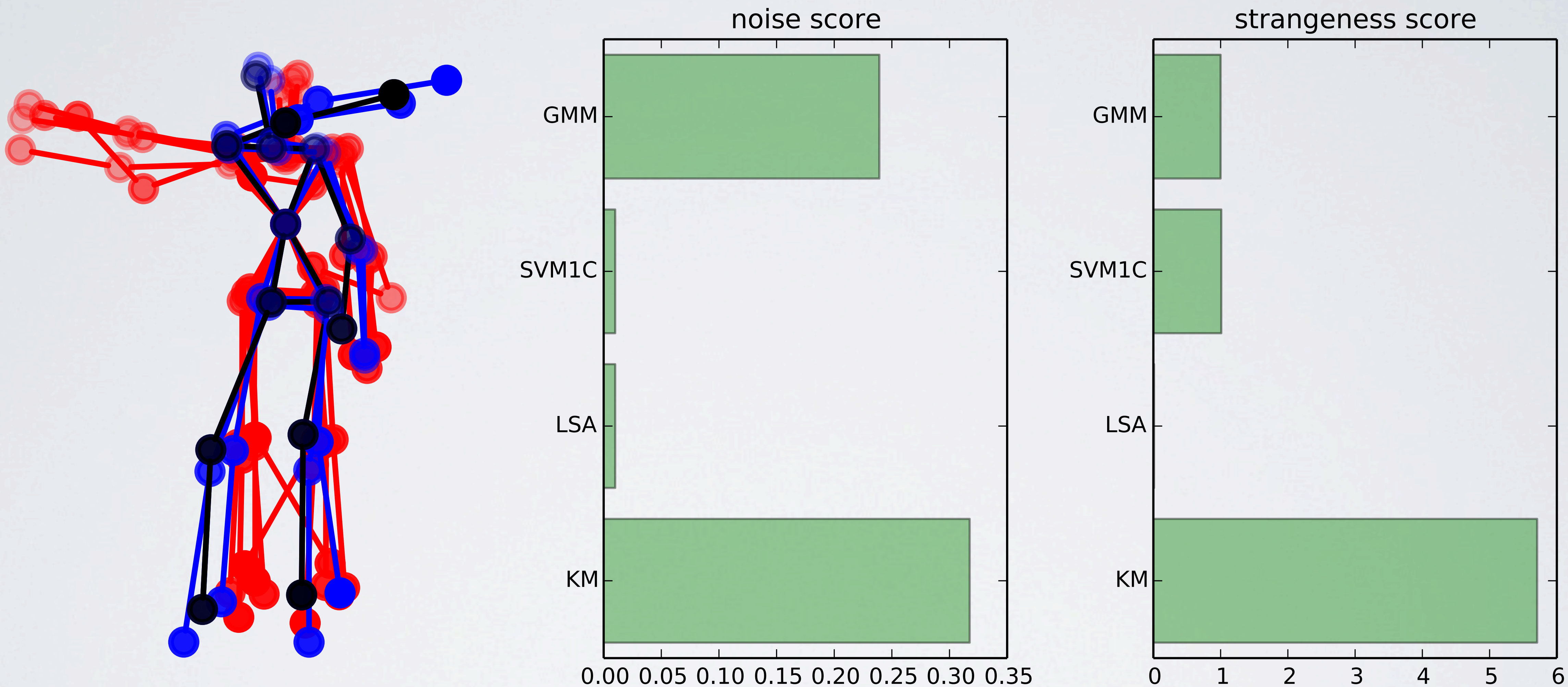


Observed poses (previous sessions)

Current observed pose

Observed poses (during session)

LET'S SEE AN EXAMPLE

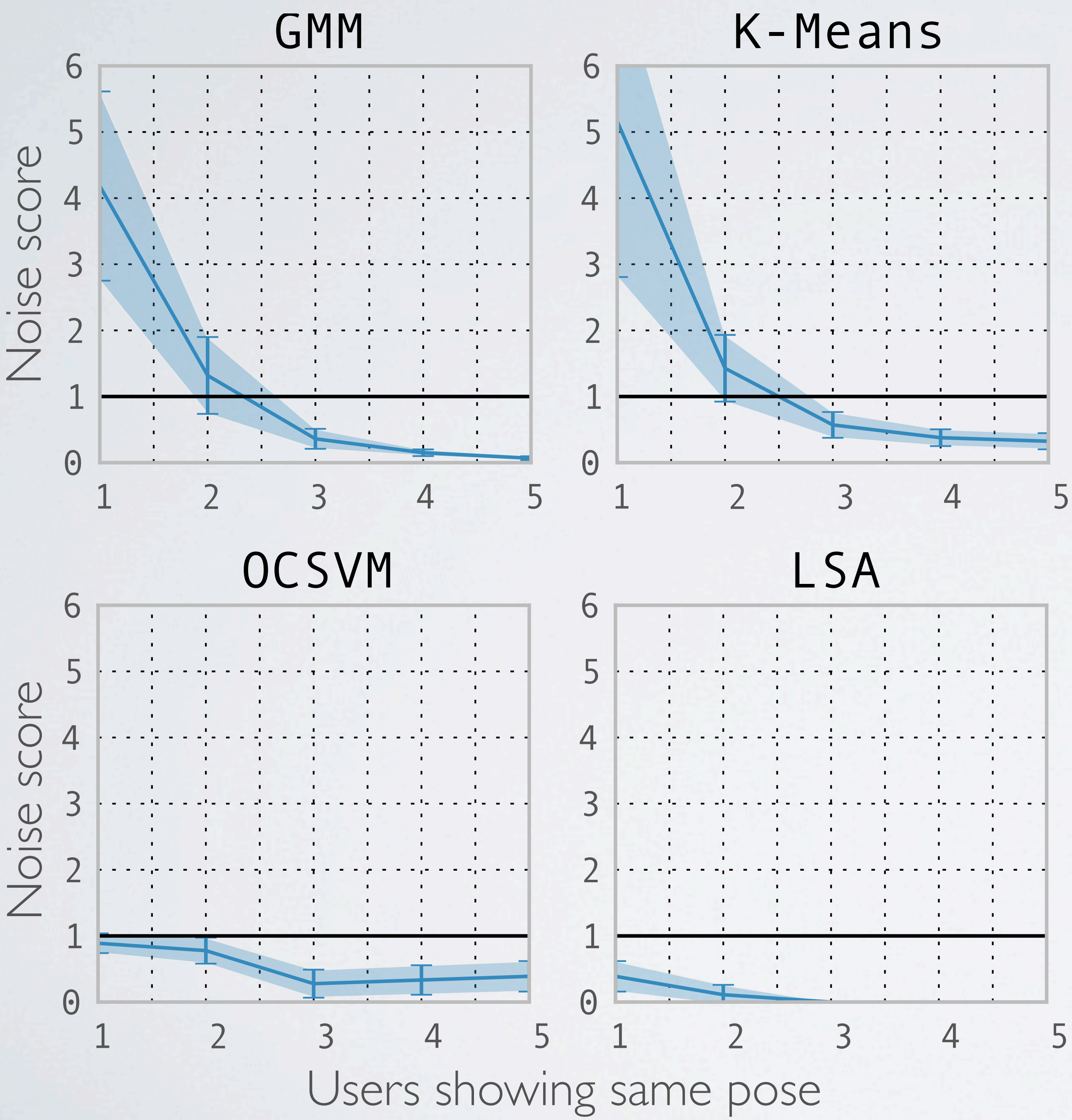


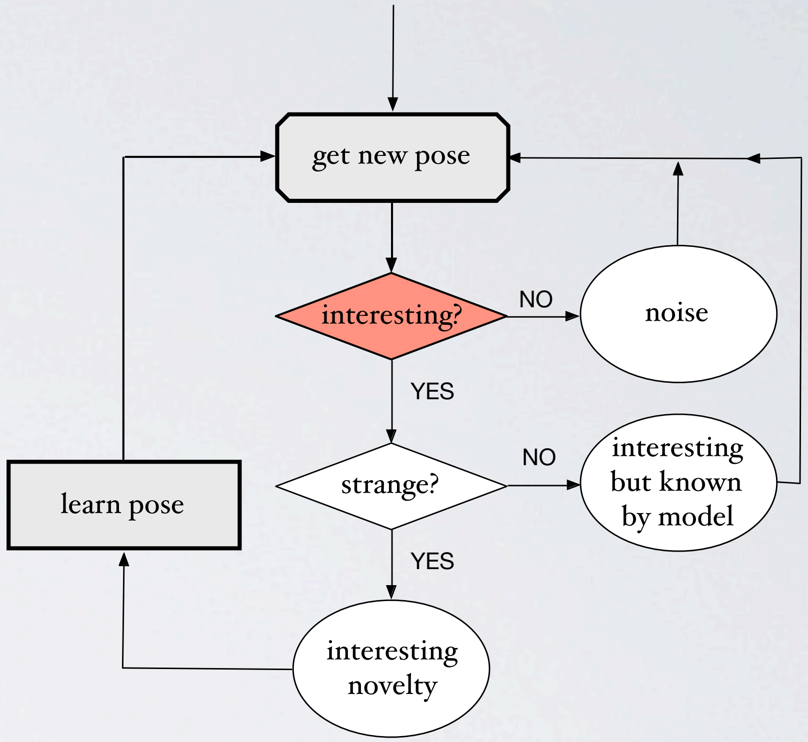
Observed poses (previous sessions)

Current observed pose

Observed poses (during session)

NOISE FILTER

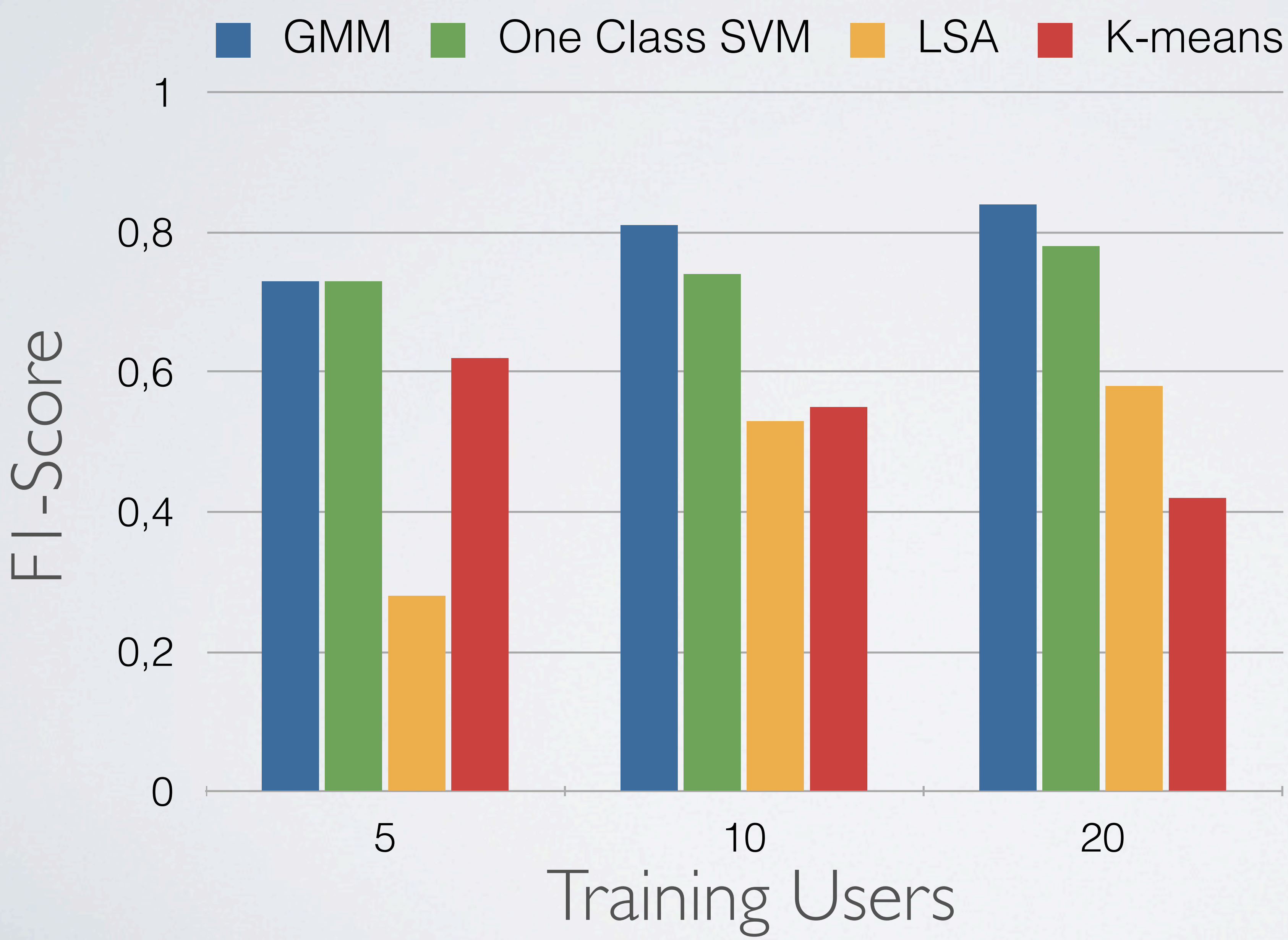


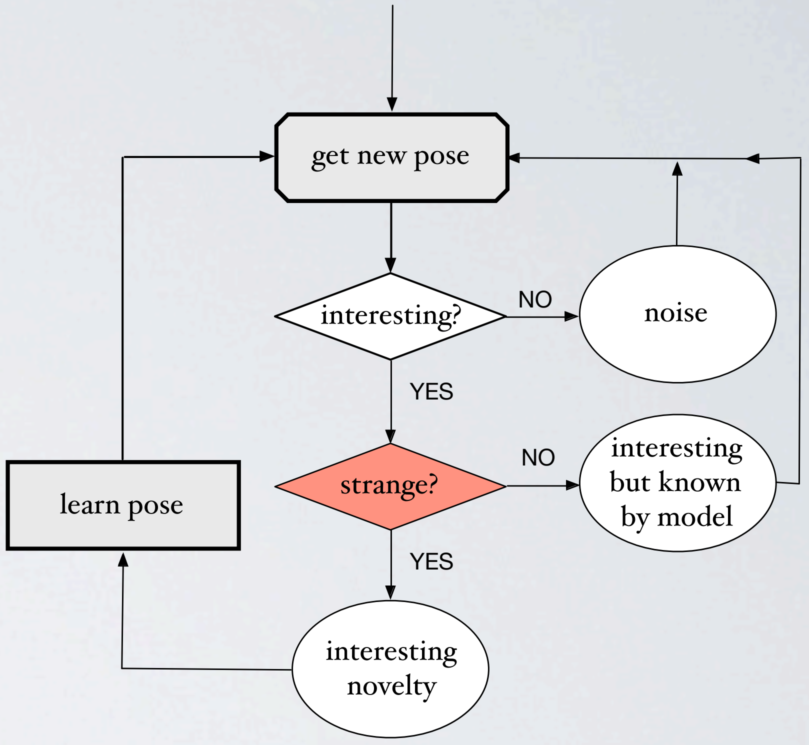


Deciding when new instances start to become interesting by forming *clusters*.

STRANGENESS EVALUATION

Detecting "novelties"





CONCLUSION

Proof of concept

Curiosity factor still needs to be calculated and studied experimentally

Study our approach in other applications

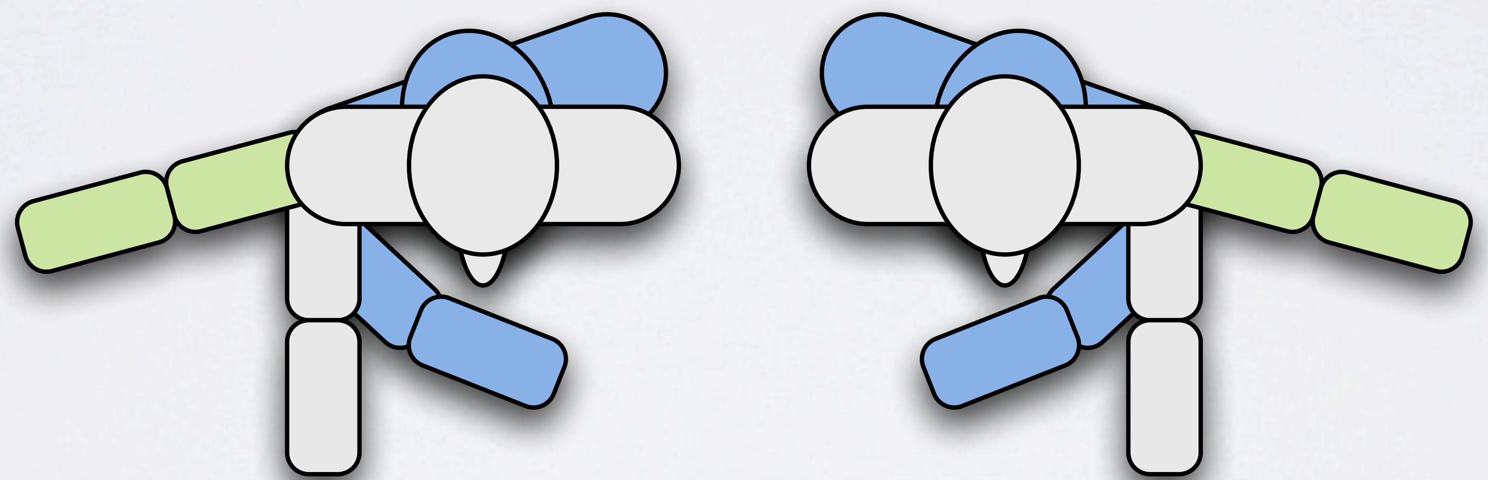
PUBLISHED RESULTS

- **V. Gonzalez-Pacheco**, A. Sanz, M. Malfaz, and M. a. Salichs, "*Novelty Detection for Interactive Pose Recognition by a Social Robot*," Int. J. Adv. Robot. Syst., vol. 12, no. 43, p. 1, 2015.

- **V. Gonzalez-Pacheco**, A. Sanz, M. Malfaz, and M. A. Salichs, "*Using novelty detection in HRI: Enabling robots to detect new poses and actively ask for their labels*," in 2014 IEEE-RAS International Conference on Humanoid Robots, 2014, pp. 1110–1115.

INTERACTIVE AND ACTIVE LEARNING

NOVELTY DETECTION



Introduction

Part I: Interactive Learning

Poses

Objects

Part II: Interactive and Active Learning

Poses

Objects

Novelties

Conclusions

CONCLUSIONS

CONCLUSIONS

"To ***develop a system that enables a social robot to learn interactively in a natural way****, similarly to how a person would learn from another person."*

KEY CONTRIBUTIONS
INTERACTIVE LEARNING

Developed a system that enables robots to learn while interacting

2 Different approaches

- Grammar-based
- Dialogue-based (+ NLP)

KEY CONTRIBUTIONS

ACTIVE LEARNING

Studied how innacurate user's answers might impact learning

Extended Filter mitigates this problem

Robot uses AL to keep learning after the training session ends by asking questions when its is uncertain

Robot can learn new concepts

FUTURE WORKS

INTERACTION

Study how robot learning is perceived by humans

ACTIVE LEARNING

Continuous learning

Apply to other domains

LIST OF PUBLICATIONS

JOURNALS

- **V. Gonzalez-Pacheco**, A. Sanz, M. Malfaz, and M. a. Salichs, "*Novelty Detection for Interactive Pose Recognition by a Social Robot*," Int. J. Adv. Robot. Syst., vol. 12, no. 43, p. 1, 2015.
- **V. Gonzalez-Pacheco**, M. Malfaz, F. Fernandez, and M. A. Salichs, "*Teaching human poses interactively to a social robot*," Sensors, vol. 13, no. 9, pp. 12406–12430, 2013.
- **V. Gonzalez-Pacheco**, A. Ramey, F. Alonso-Martin, A. Castro-Gonzalez, and M. A. Salichs, "*Maggie: A Social Robot as a Gaming Platform*," Int. J. Soc. Robot., vol. 3, no. 4, pp. 371–381, Sep. 2011.

CONFERENCES (I)

- **V. Gonzalez-Pacheco**, A. Sanz, M. Malfaz, and M. A. Salichs, "*Using novelty detection in HRI: Enabling robots to detect new poses and actively ask for their labels*," in 2014 IEEE-RAS International Conference on Humanoid Robots, 2014, pp. 1110–1115.
- **V. Gonzalez-Pacheco**, M. Malfaz, and M. A. Salichs, "*Asking rank queries in pose learning*," in Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction - HRI '14, 2014, pp. 164–165.
- **V. Gonzalez-Pacheco** and M. A. Salichs, "*Active Learning for Pose Recognition. Studying what and when to ask for Feature Queries*," in Proc of the 8th HRI Pioneers Workshop, 2013, pp. 3–4.

CONFERENCES (II)

- J. Sequeira, P. Lima, A. Saffiotti, **V. Gonzalez-Pacheco**, and M. A. Salichs, "*MOnarCH: Multi-Robot Cognitive Systems Operating in Hospitals*," in Proc of the ICRA 2013 Workshop on Crossing the Reality Gap – From Single to Multi to Many Robot Systems, 2013, p. 1.

- A. Valero-Gomez, J. Gonzalez-Gomez, **V. Gonzalez-Pacheco**, and M. A. Salichs, "*Printable creativity in plastic valley UC3M*," in Proceedings of the 2012 IEEE Global Engineering Education Conference (EDUCON), 2012, pp. 1–9.

- A. Ramey, **V. González-Pacheco**, and M. A. Salichs, "*Integration of a low-cost RGB-D sensor in a social robot for gesture recognition*," in Proceedings of the 6th international conference on Human-Robot Interaction - HRI '11, 2011, pp. 229–230.

- F. Alonso-Martin, **V. Gonzalez-Pacheco**, A. Castro-Gonzalez, A. A. Ramey, M. Yébenes, and M. A. Salichs,"*Using a social robot as a gaming platform*," in 2nd International Conference on Social Robotics, 2010, pp. 30–39.

ONGOING PUBLICATIONS

- **Victor Gonzalez-Pacheco**, María Malfaz, Álvaro Castro-González, Miguel A. Salichs. *How Much should a Social Robot trust the user feedback? Analyzing the impact of Verbal Answers in Active Learning*. Int. Journal Social Robotics. 2015 [UNDER REVIEW]
- **Victor Gonzalez Pacheco**, Maria Malfaz, Miguel A. Salichs. *Active Learning for in-hand Object Recognition*. Sensors. 2016. [IN PREPARATION]

SOURCE CODE

https://github.com/UC3MSocialRobots/pose_tracker_stack

https://github.com/UC3MSocialRobots/ocular_project

https://github.com/UC3MSocialRobots/rospy_utils

DATASETS:

https://github.com/VGonPa/datasets-poses2012

INTERACTIVE AND ACTIVE LEARNING FOR SOCIAL ROBOTICS

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Advisers: Miguel Ángel Salichs
María Malfaz

Universidad
Carlos III de Madrid

Leganés, November 2015