# Using Perceptual Context to Ground Language


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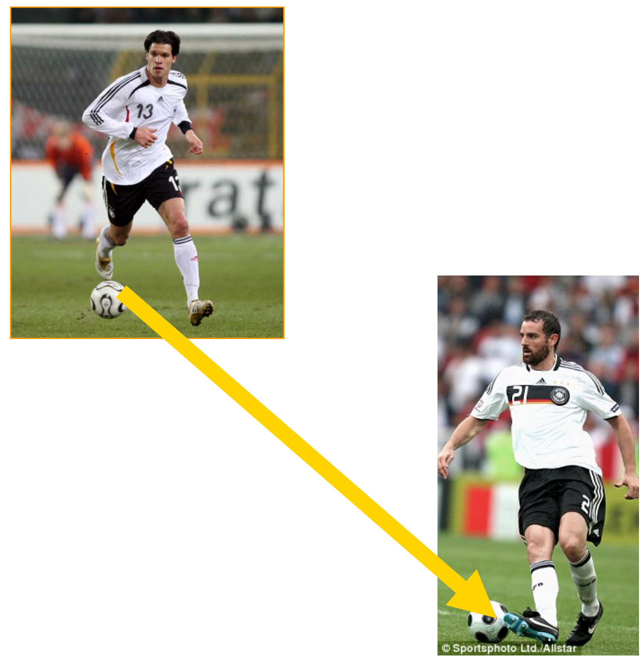
# Learning Language from Perceptual Context

- Children do not learn language from annotated corpora.
- The natural way to learn language is to perceive language in the context of its use in the physical and social world.

# Challenge



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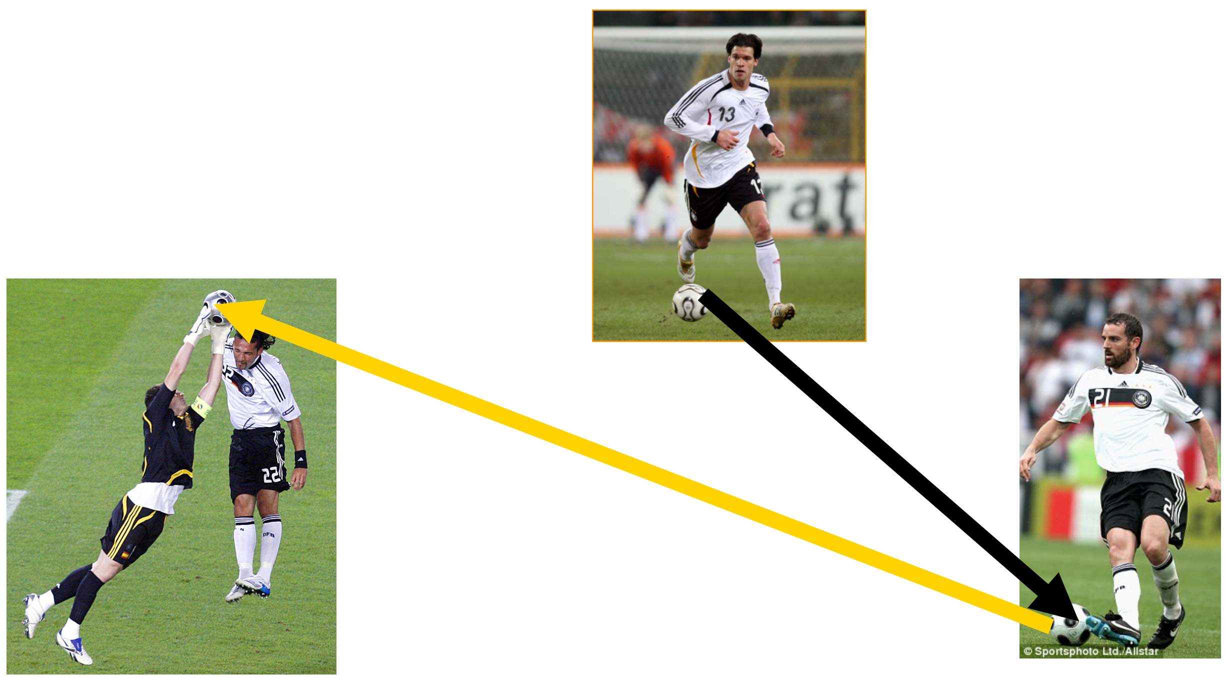
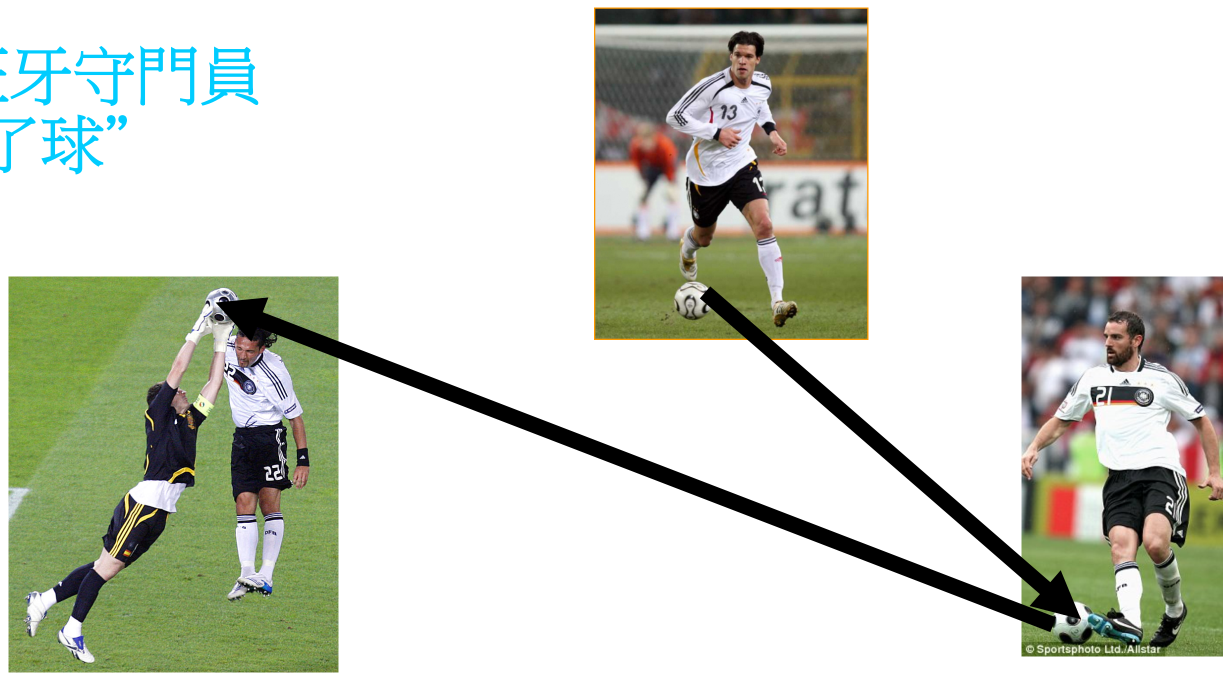


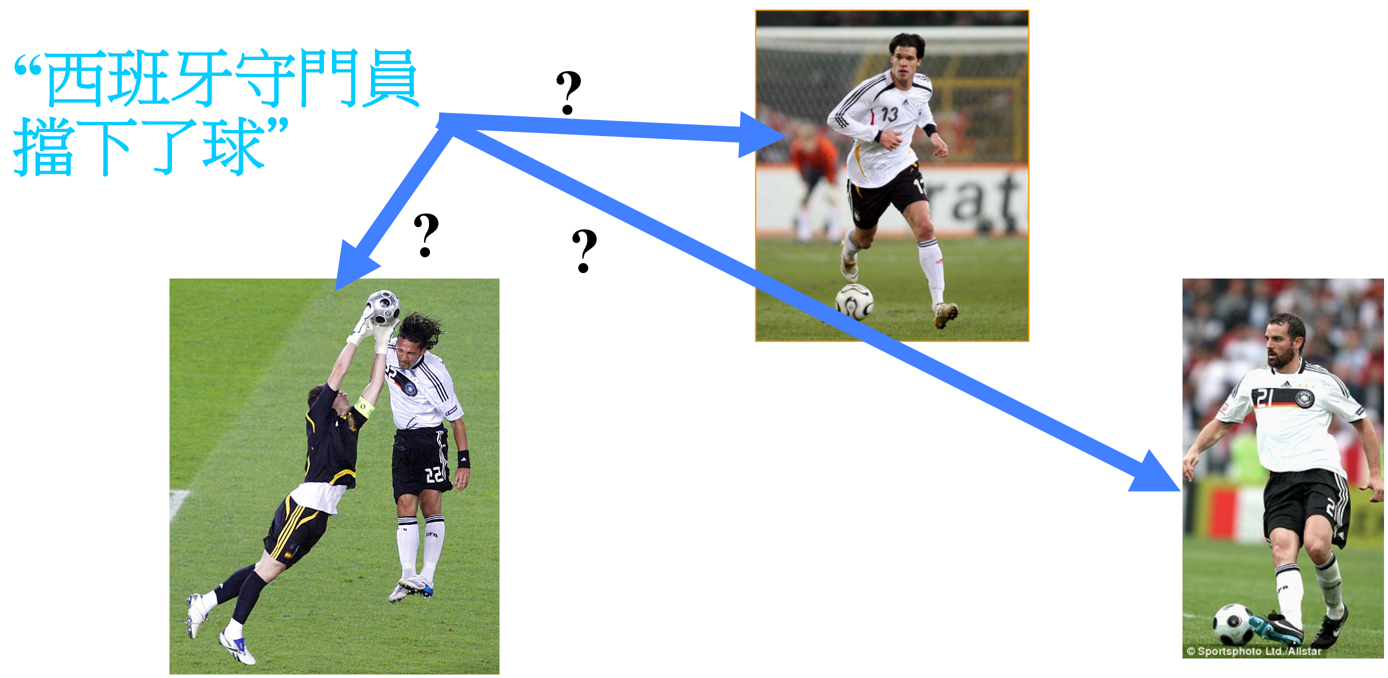
# Challenge

“西班牙守門員
擋下了球”



# Challenge

A linguistic input may correspond to many possible events



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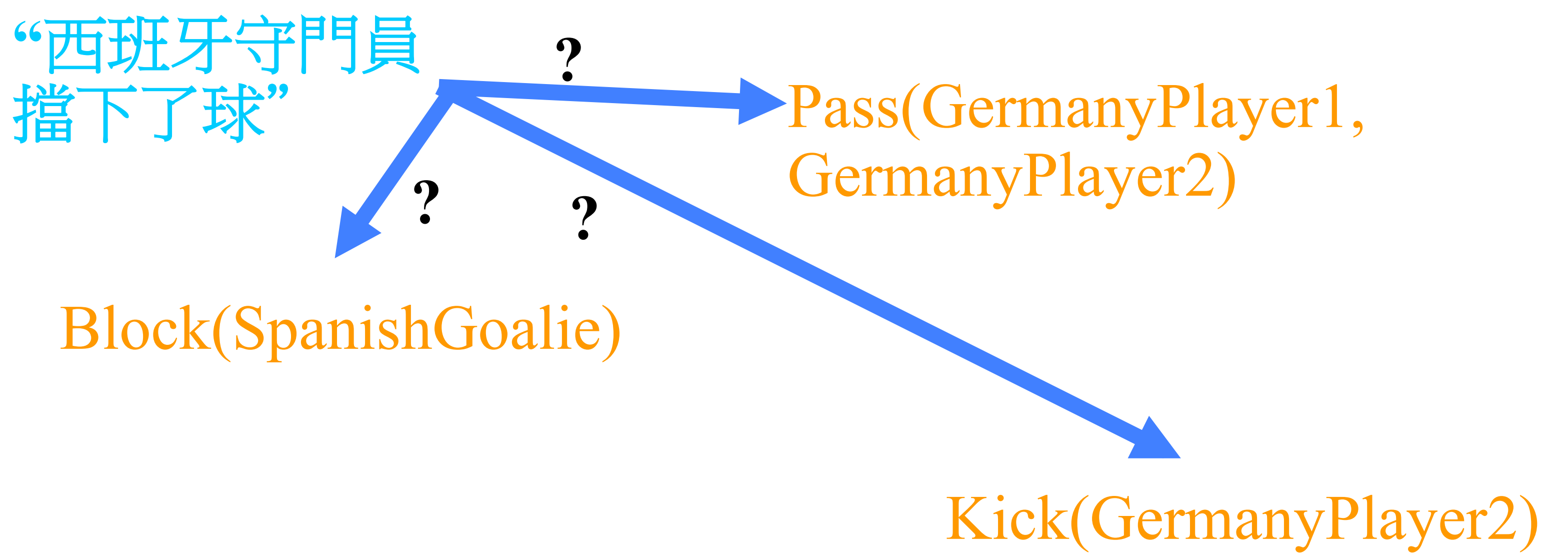


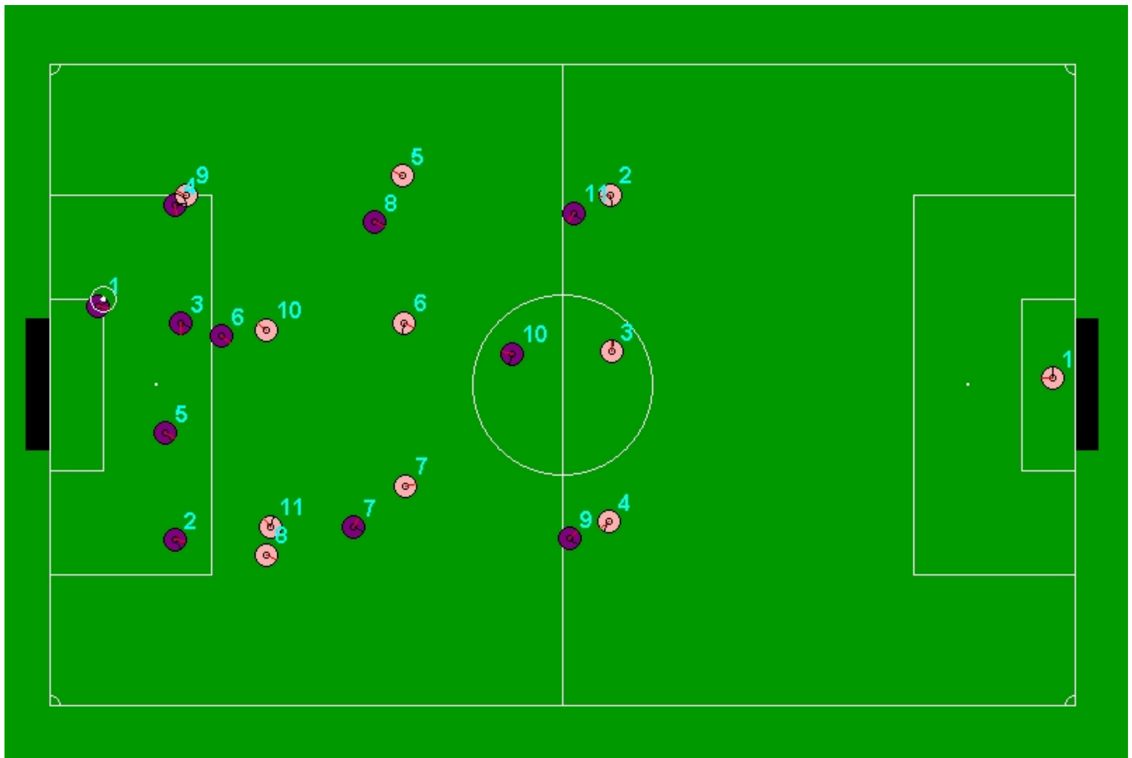
# Overview

- **Sportscasting task**
- Tactical generation
- Human evaluation

# Tractable Challenge Problem: Learning to Be a Sportscaster

- **Goal**: Learn from realistic data of natural language used in a representative context while avoiding difficult issues in computer perception (i.e. speech and vision).
- **Solution**: Learn from textually annotated traces of activity in a simulated environment.
- **Example**: Traces of games in the Robocup simulator paired with textual sportscaster commentary.

# Robocup Simulation League



Purple goalie blocked the ball

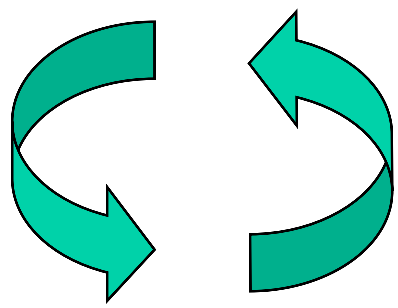
# Learning to Sportscast

- Learn to sportscast by observing sample human sportscasts
- Build a function that maps between natural language (NL) and meaning representation (MR)
  - NL: Textual commentaries about the game
  - MR: Predicate logic formulas that represent events in the game

# Mapping between NL/MR

NL: “Purple3 passes the ball to Purple5”

Semantic Parsing
(NL → MR)



Tactical Generation
(MR → NL)

MR: Pass ( Purple3, Purple5 )

# Robocup Sportscaster Trace

| Natural Language Commentary | Meaning Representation |
| --- | --- |
| | badPass ( Purple1, Pink8 ) |
| Purple goalie turns the ball over to Pink8 | turnover ( Purple1, Pink8 ) |
| | kick ( Pink8) |
| Purple team is very sloppy today | pass ( Pink8, Pink11 ) |
| Pink8 passes the ball to Pink11 | kick ( Pink11 ) |
| Pink11 looks around for a teammate | kick ( Pink11 ) |
| | ballstopped |
| Pink11 makes a long pass to Pink8 | kick ( Pink11 ) |
| | pass ( Pink11, Pink8 ) |
| | kick ( Pink8 ) |
| Pink8 passes back to Pink11 | pass ( Pink8, Pink11 ) |

# Robocup Sportscaster Trace

**Natural Language Commentary**

Purple goalie turns the ball over to Pink8

Purple team is very sloppy today

Pink8 passes the ball to Pink11

Pink11 looks around for a teammate

Pink11 makes a long pass to Pink8

Pink8 passes back to Pink11

**Meaning Representation**

badPass ( Purple1, Pink8 )

turnover ( Purple1, Pink8 )

kick ( Pink8)

pass ( Pink8, Pink11 )

kick ( Pink11 )

kick ( Pink11 )

ballstopped

kick ( Pink11 )

pass ( Pink11, Pink8 )

kick ( Pink8 )

pass ( Pink8, Pink11 )

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Pink8 passes back to Pink11

**Meaning Representation**

P6 ( C1, C19 )

P5 ( C1, C19 )

P1( C19 )

P2 ( C19, C22 )

P1 ( C22 )

P1 ( C22 )

P0

P1 ( C22 )

P2 ( C22, C19 )

P1 ( C19 )

P2 ( C19, C22 )

# Robocup Data

- Collected human textual commentary for the 4 Robocup championship games from 2001-2004.
  - Avg # events/game = 2,613
  - Avg # English sentences/game = 509
  - Avg # Korean sentences/game = 499
- Each sentence matched to all events within previous 5 seconds.
  - Avg # MRs/sentence = 2.5 (min 1, max 12)
- Manually annotated with correct matchings of sentences to MRs (for evaluation purposes only).

# Overview

- Sportscasting task
- **Tactical generation**
- Human evaluation

# Tactical Generation

- Learn how to generate NL from MR
- Example:

  Pass(Pink2, Pink3) → “Pink2 kicks the ball to Pink3”

- Two steps
  1. Disambiguate the training data
  2. Learn a language generator

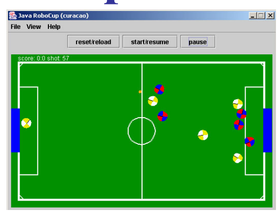
# WASP: **W**ord **A**lignment-based **S**emantic **P**arsing

- Uses statistical machine translation techniques
  - Synchronous context-free grammars (SCFG) [Wu, 1997; Melamed, 2004; Chiang, 2005]
  - Word alignments [Brown et al., 1993; Och & Ney, 2003]
- SCFG supports both:
  - Semantic Parsing: NL $\rightarrow$ MR
  - Tactical Generation: MR $\rightarrow$ NL

# WASPER: **WASP** with **EM**-like **R**etraining

**Sportscaster**

**Robocup Simulator**




Purple7 loses the ball to Pink2

Pink2 kicks the ball to Pink5

Pink5 makes a long pass to Pink8

Pink8 shoots the ball

Pass ( Purple5, Purple7 )
Turnover ( purple7 , pink2 )
Kick ( pink2 )
Pass ( pink2 , pink5 )
Kick ( pink5 )

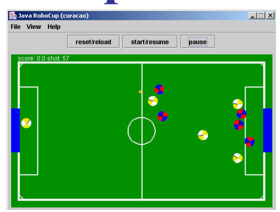
Pass ( pink5 , pink8)
Ballstopped
Kick ( pink8 )

Ambiguous Training Data

# WASPER: **WASP** with **EM**-like **R**etraining

Sportscaster

Robocup Simulator

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Pink8 shoots the ball

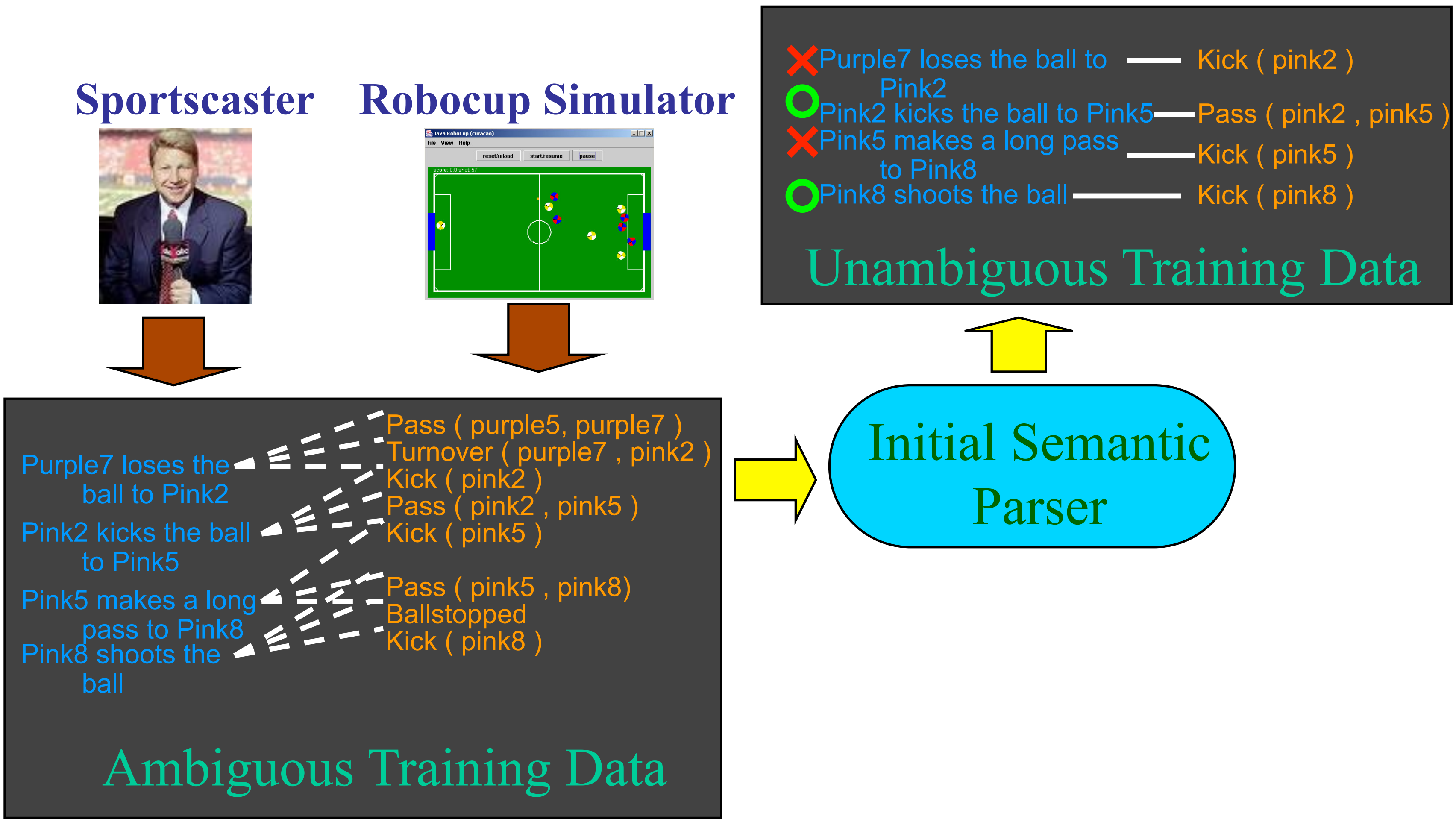
Pass ( Purple5, Purple7 )
Turnover ( purple7 , pink2 )
Kick ( pink2 )
Pass ( pink2 , pink5 )
Kick ( pink5 )
Pass ( pink5 , pink8)
Ballstopped
Kick ( pink8 )

Ambiguous Training Data

WASP

Initial Semantic Parser

# WASPER: **WASP** with **EM**-like **R**etraining



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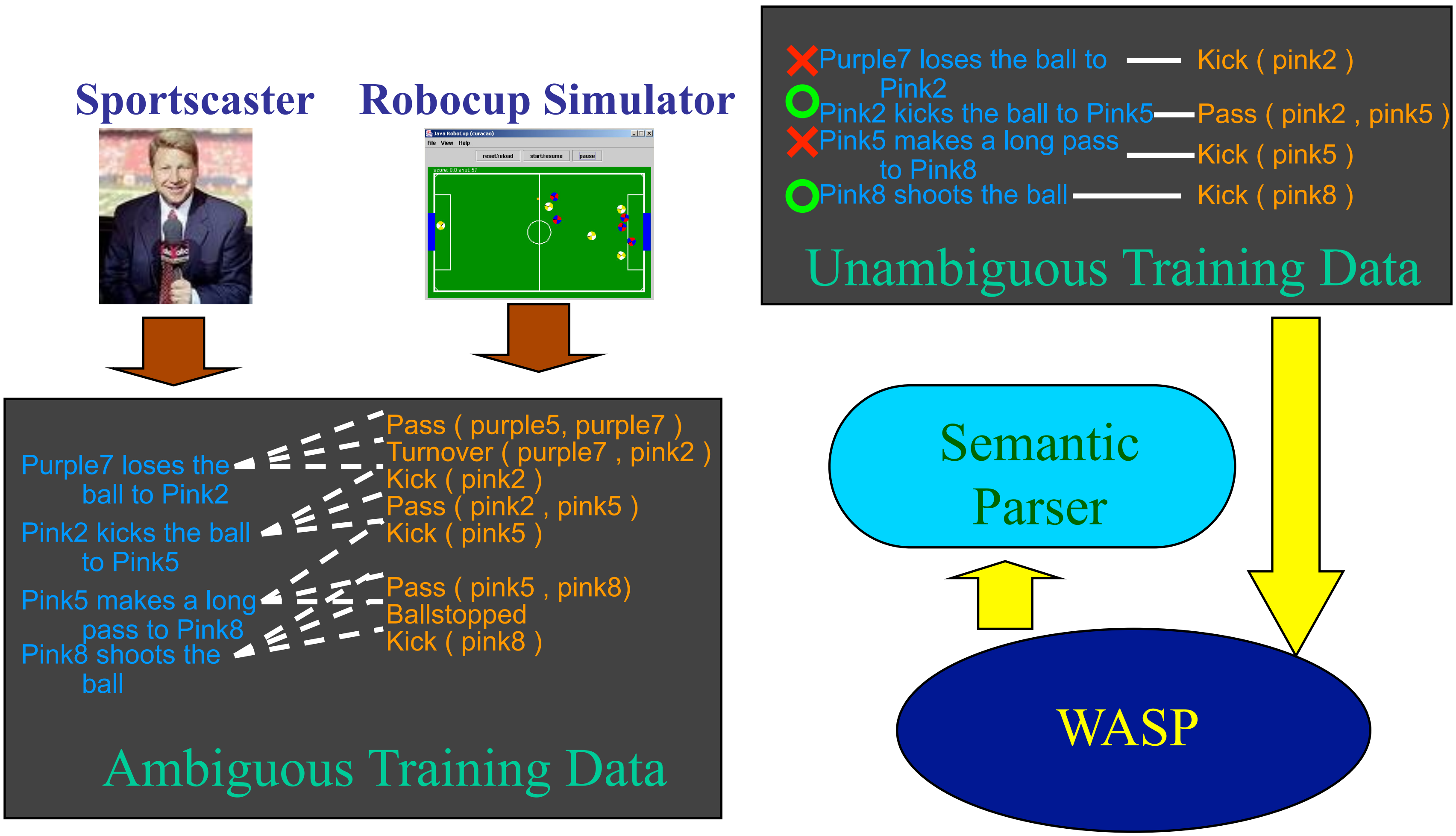

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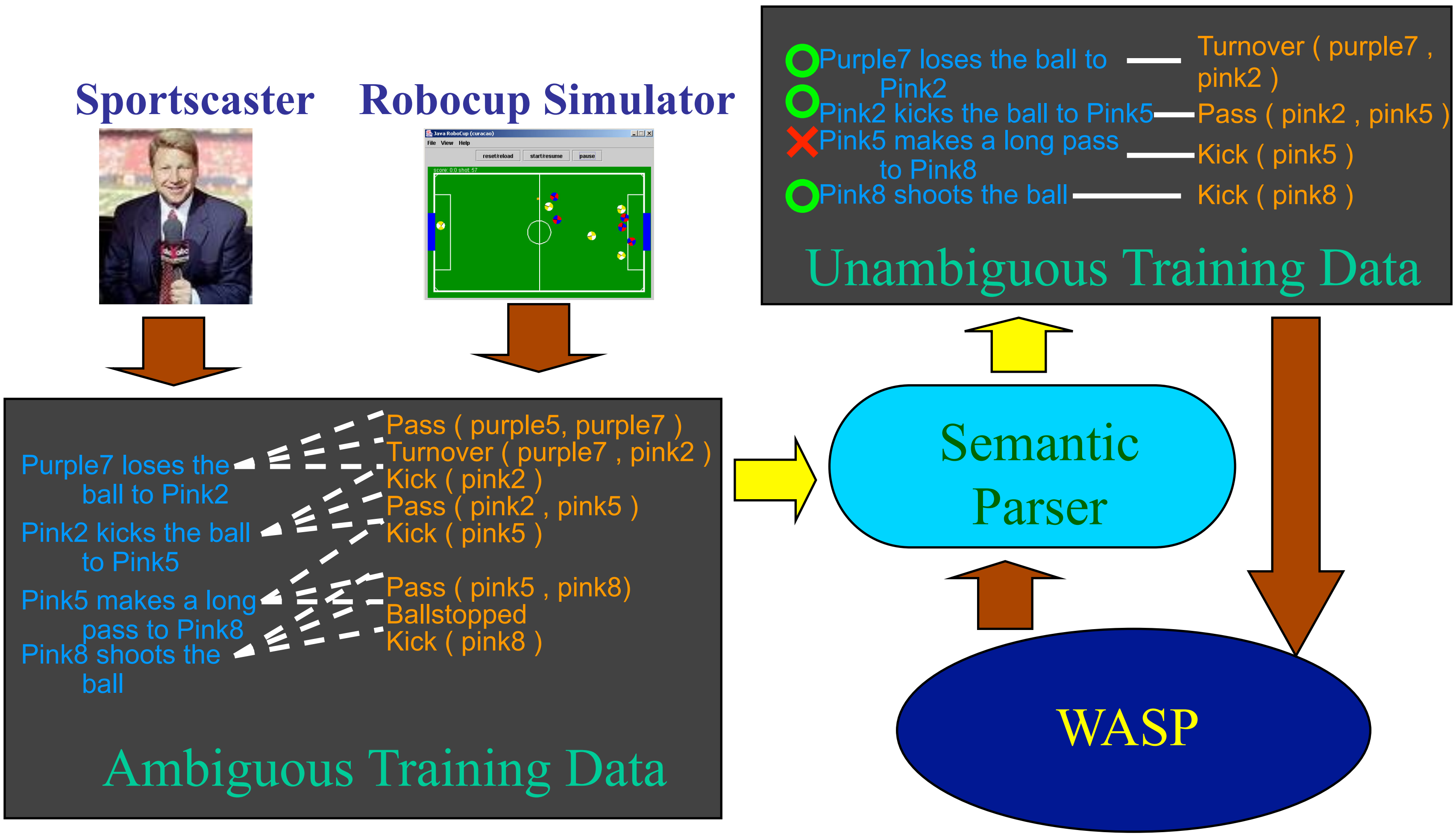
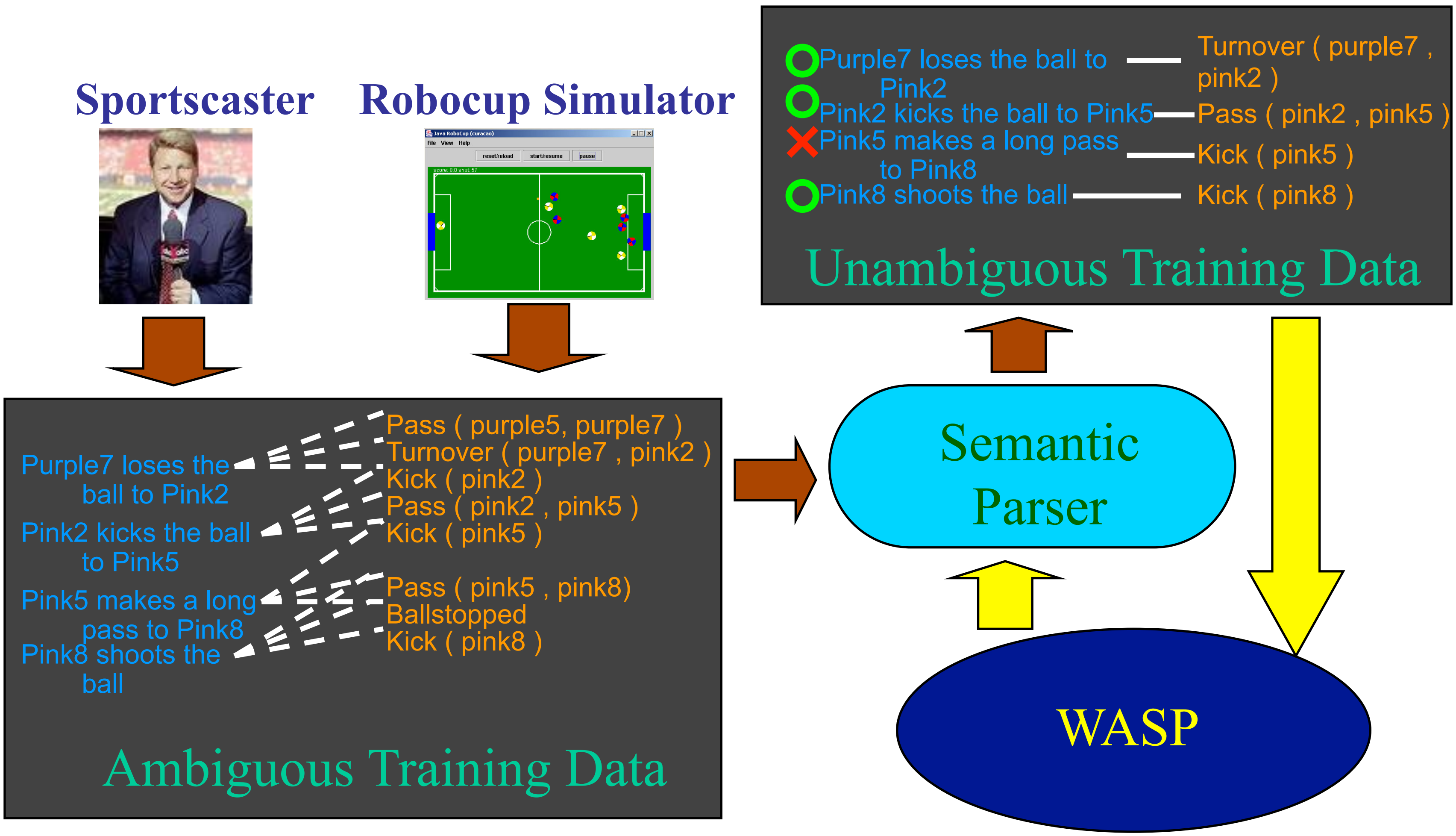
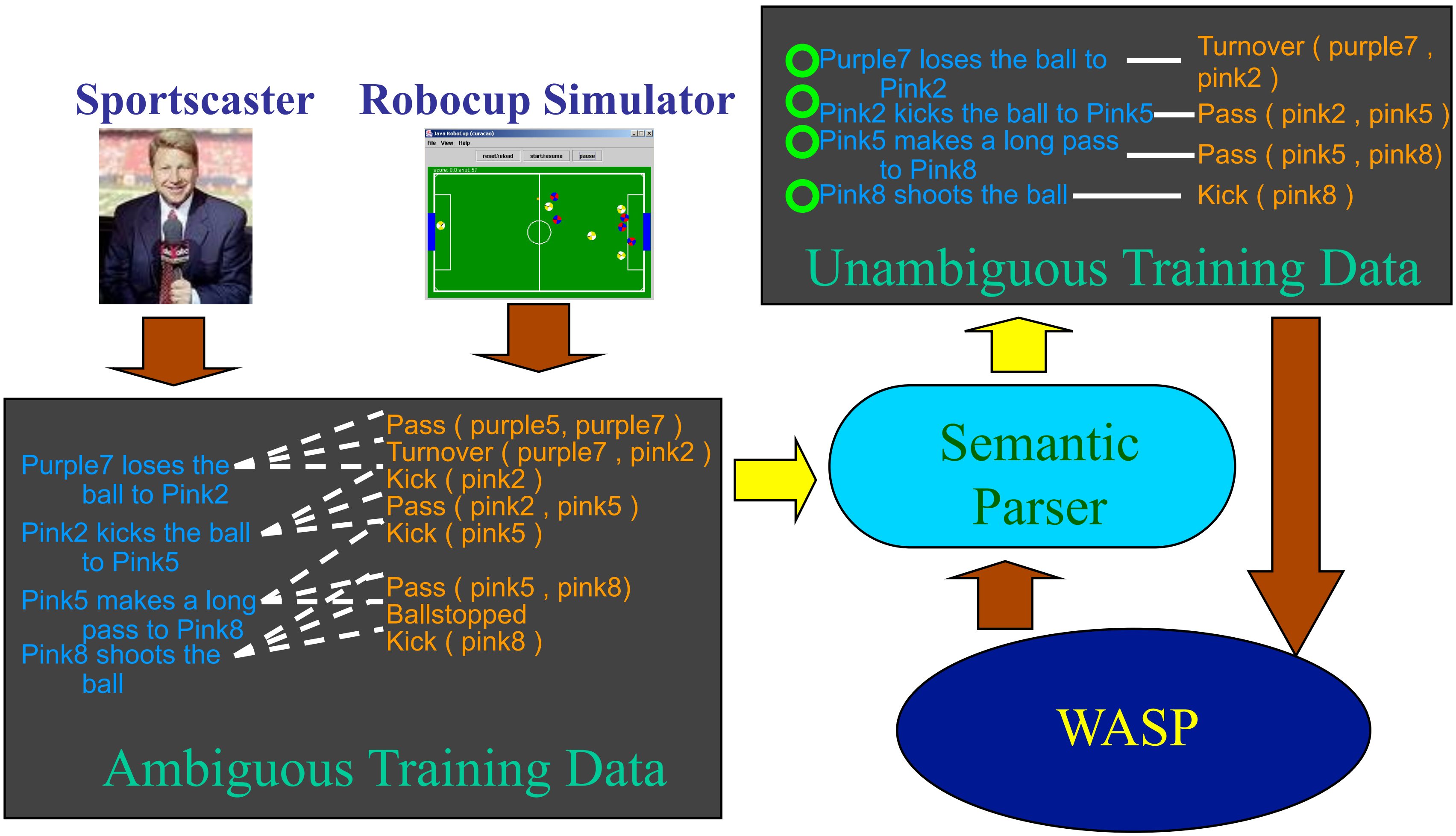


# WASPER: **WASP** with **E**M-like **R**etraining



# WASPER: **WASP** with **EM**-like **R**etraining



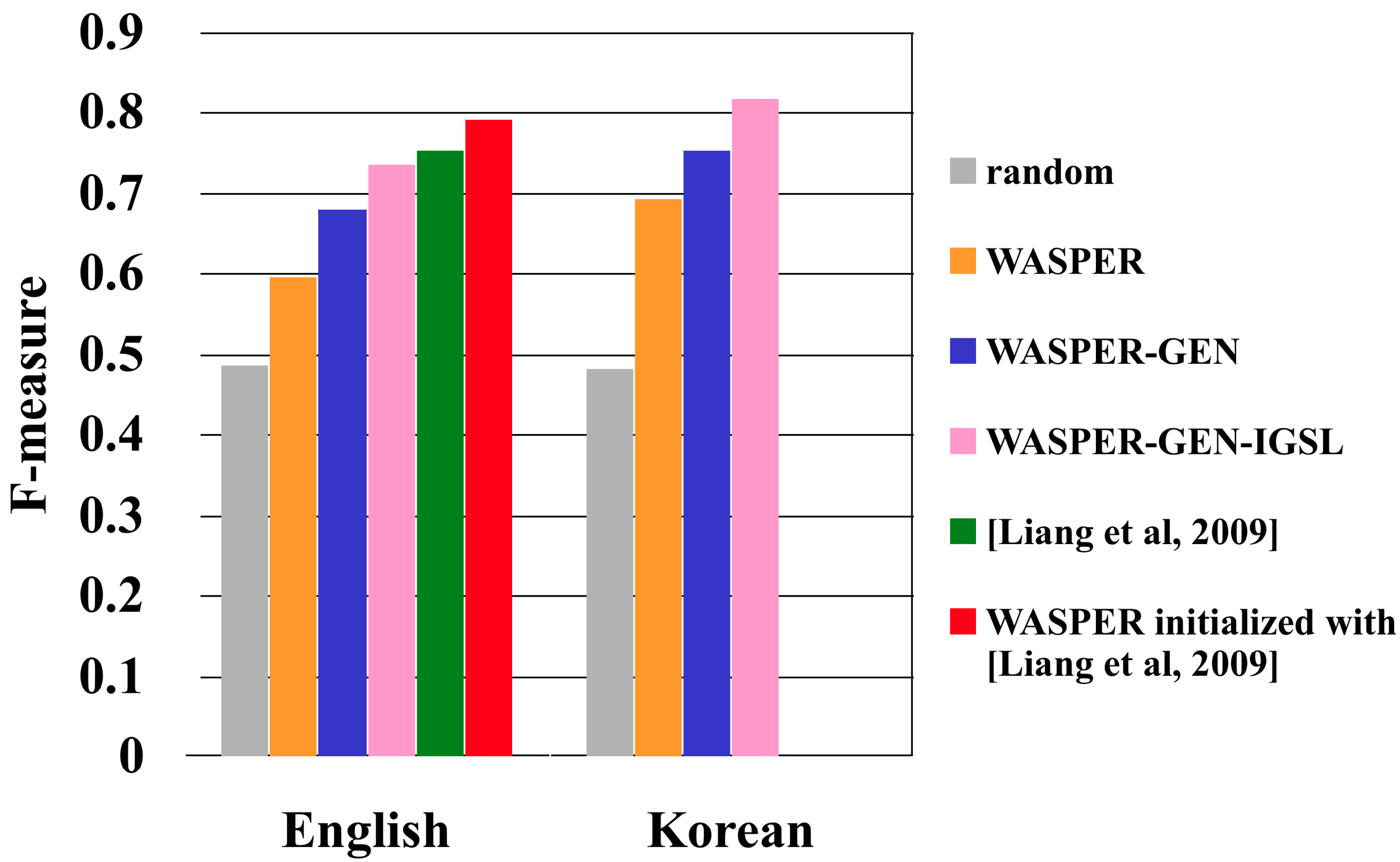
# Additional Systems

- WASPER-GEN
  - Uses tactical generator instead of semantic parser
- WASPER-GEN-IGSL
  - Same as WASPER-GEN except uses Iterative Generation Strategy Learning (IGSL) to initialize the first iteration
- WASP with random matching (lower baseline)
- WASP with gold matching (upper baseline)

# Matching

- 4 Robocup championship games from 2001-2004.
  - Avg # events/game = 2,613
  - Avg # English sentences/game = 509
  - Avg # Korean sentences/game = 499
- Leave-one-game-out cross-validation
- Metric:
  - **Precision**: % of system's annotations that are correct
  - **Recall**: % of gold-standard annotations produced
  - **F-measure**: Harmonic mean of precision and recall

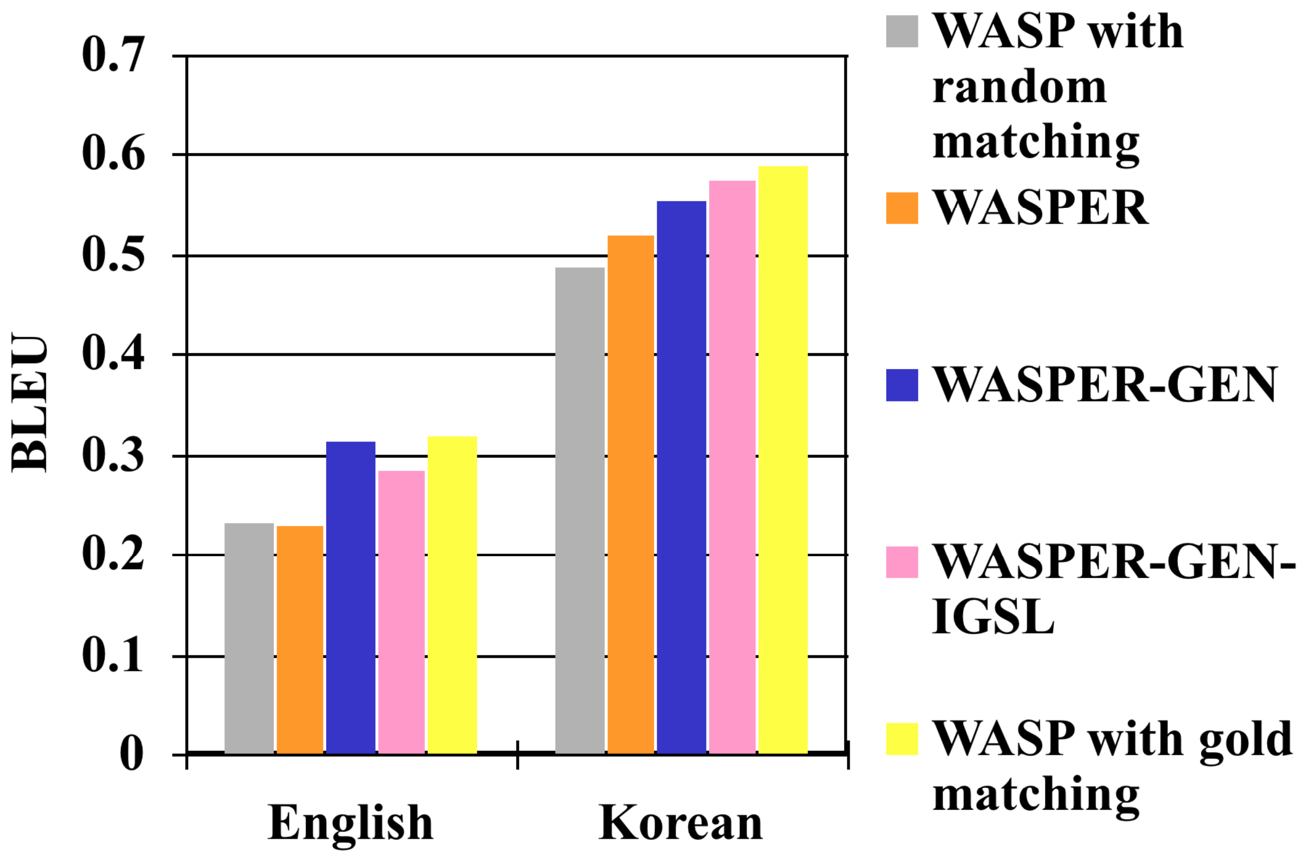
# Matching Results



# Tactical Generation

- Measure how accurately NL generator produces English sentences for chosen MRs in the test games.
- Use gold-standard matches to determine the correct sentence for each MR that has one.
- Leave-one-game-out cross-validation
- Metric:
  - **BLEU score:** [Papineni et al, 2002], N=4

# Tactical Generation Results



# Overview

- Sportscasting task
- Tactical generation
- **Human evaluation**

# Human Evaluation

- Used Amazon's Mechanical Turk to recruit human judges (~40 judges per video)
- 8 commented game clips
  - 4 minute clips randomly selected from each of the 4 games
  - Each clip commented once by a human, and once by the machine
- Presented in random counter-balanced order
- Judges were not told which ones were human or machine generated

# Human Evaluation

| Score | English Fluency | Semantic Correctness | Sportscasting Ability |
|---|---|---|---|
| 5 | Flawless | Always | Excellent |
| 4 | Good | Usually | Good |
| 3 | Non-native | Sometimes | Average |
| 2 | Disfluent | Rarely | Bad |
| 1 | Gibberish | Never | Terrible |

# Human Evaluation

| | Syntax | Semantic | Overall | Human? |
|---|---|---|---|---|
| 2001 Human | 3.735 | 3.588 | 3.147 | 0.206 |
| 2001 Machine | 3.888 | 3.806 | 3.611 | 0.4 |
| 2002 Human | 4.132 | 4.579 | 4.027 | 0.421 |
| 2002 Machine | 3.971 | 3.735 | 3.286 | 0.118 |
| 2003 Human | 3.541 | 3.730 | 2.611 | 0.135 |
| 2003 Machine | 3.893 | 4.263 | 3.368 | 0.193 |
| 2004 Human | 4.029 | 4.171 | 3.543 | 0.2 |
| 2004 Machine | 4.125 | 4.375 | 4.0 | 0.563 |

# Conclusion

- Current language learning work uses expensive, annotated training data.
- We have developed a language learning system that can learn from language paired with an ambiguous perceptual environment.
- We have evaluated it on the task of learning to sportscast simulated Robocup games.
- The system learns to sportscast as well as CS students who don’t watch soccer

# Demo Clip

- Game clip commentated using WASPER-GEN with IGSL, since this gave the best results for generation.
- FreeTTS was used to synthesize speech from textual output.
- YouTube link:

  http://www.youtube.com/watch?v=L_MIRS7NBpU

# Backup Slides

# Overview

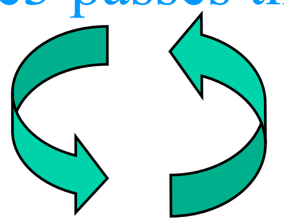
- Sportscasting task
- **Related works**
- Tactical generation
- Strategic generation
- Human evaluation

# Semantic Parser Learners

- Learn a function from NL to MR

NL: "Purple3 passes the ball to Purple5"

Semantic Parsing
(NL → MR)



Tactical Generation
(MR → NL)

MR: Pass ( Purple3, Purple5 )

- We experiment with two semantic parser learners
  - WASP (Wong & Mooney, 2006; 2007)
  - KRISP (Kate & Mooney, 2006)

# KRISP: **K**ernel-based **R**obust **I**nterpretation by **S**emantic **P**arsing

- Productions of MR language are treated like semantic concepts
- SVM classifier is trained for each production with string subsequence kernel
- These classifiers are used to compositionally build MRs of the sentences
- More resistant to noisy supervision but incapable of tactical generation

# Overview

- Sportscasting task
- Related works
- Tactical generation
- **Strategic generation**
- Human evaluation

# Strategic Generation

- Generation requires not only knowing ***how*** to say something (tactical generation) but also ***what*** to say (strategic generation).
- For automated sportscasting, one must be able to effectively choose which events to describe.

# Example of Strategic Generation

pass ( purple7 , purple6 )

ballstopped

kick ( purple6 )

pass ( purple6 , purple2 )

ballstopped

kick ( purple2 )

pass ( purple2 , purple3 )

kick ( purple3 )

badPass ( purple3 , pink9 )

turnover ( purple3 , pink9 )

# Example of Strategic Generation

**pass ( purple7 , purple6 )**

**ballstopped**

**kick ( purple6 )**

**pass ( purple6 , purple2 )**

**ballstopped**

**kick ( purple2 )**

**pass ( purple2 , purple3 )**

**kick ( purple3 )**

**badPass ( purple3 , pink9 )**

**turnover ( purple3 , pink9 )**

# Strategic Generation

- For each event type (e.g. pass, kick) estimate the probability that it is described by the sportscaster.
- Requires correct NL/MR matching
  - Use estimated matching from tactical generation
  - Iterative Generation Strategy Learning

# Iterative Generation Strategy Learning (IGSL)

- Directly estimates the likelihood of an event being commented on
- Self-training iterations to improve estimates
- Uses events not associated with any NL as negative evidence

# Robocup Sportscaster Trace

**Natural Language Commentary**

purple6 passes to purple2

purple3 loses the ball to pink9

purple2 makes a short pass to purple3

**Meaning Representation**

ballstopped

kick ( purple6 )

pass ( purple6 , purple2 )

turnover ( purple3 , pink9 )

kick ( purple2 )

pass ( purple2 , purple3 )

kick ( purple3 )

# Robocup Sportscaster Trace

| Natural Language Commentary | Meaning Representation |
|---|---|
| purple6 passes to purple2 | pass ( purple6 , purple2 ) |
| purple3 loses the ball to pink9 | |
| | pass ( purple2 , purple3 ) |
| purple2 makes a short pass to purple3 | |

# Robocup Sportscaster Trace

| Natural Language Commentary | Meaning Representation |
| --- | --- |
| | kick ( purple6 ) |
| purple6 passes to purple2 | |
| purple3 loses the ball to pink9 | |
| | kick ( purple2 ) |
| | kick ( purple3 ) |
| purple2 makes a short pass to purple3 | |

# Robocup Sportscaster Trace

**Natural Language Commentary**

purple6 passes to purple2

purple3 loses the ball to pink9

purple2 makes a short pass to purple3

**Meaning Representation**

kick ( purple 3 )

ballstopped

kick ( purple6 )

pass ( purple6 , purple2 )

kick ( purple2 )

turnover ( purple3 , pink9 )

kick ( purple2 )

pass ( purple2 , purple3 )

kick ( purple3 )

kick (purple 3

# Robocup Sportscaster Trace

| Natural Language Commentary | Meaning Representation |
| --- | --- |
| | kick ( purple 3 ) |
| | kick ( purple6 ) |
| purple6 passes to purple2 | |
| | kick ( purple2 ) |
| purple3 loses the ball to pink9 | |
| | kick ( purple2 ) |
| | kick ( purple3 ) |
| purple2 makes a short pass to purple3 | |
| | kick (purple 3 |

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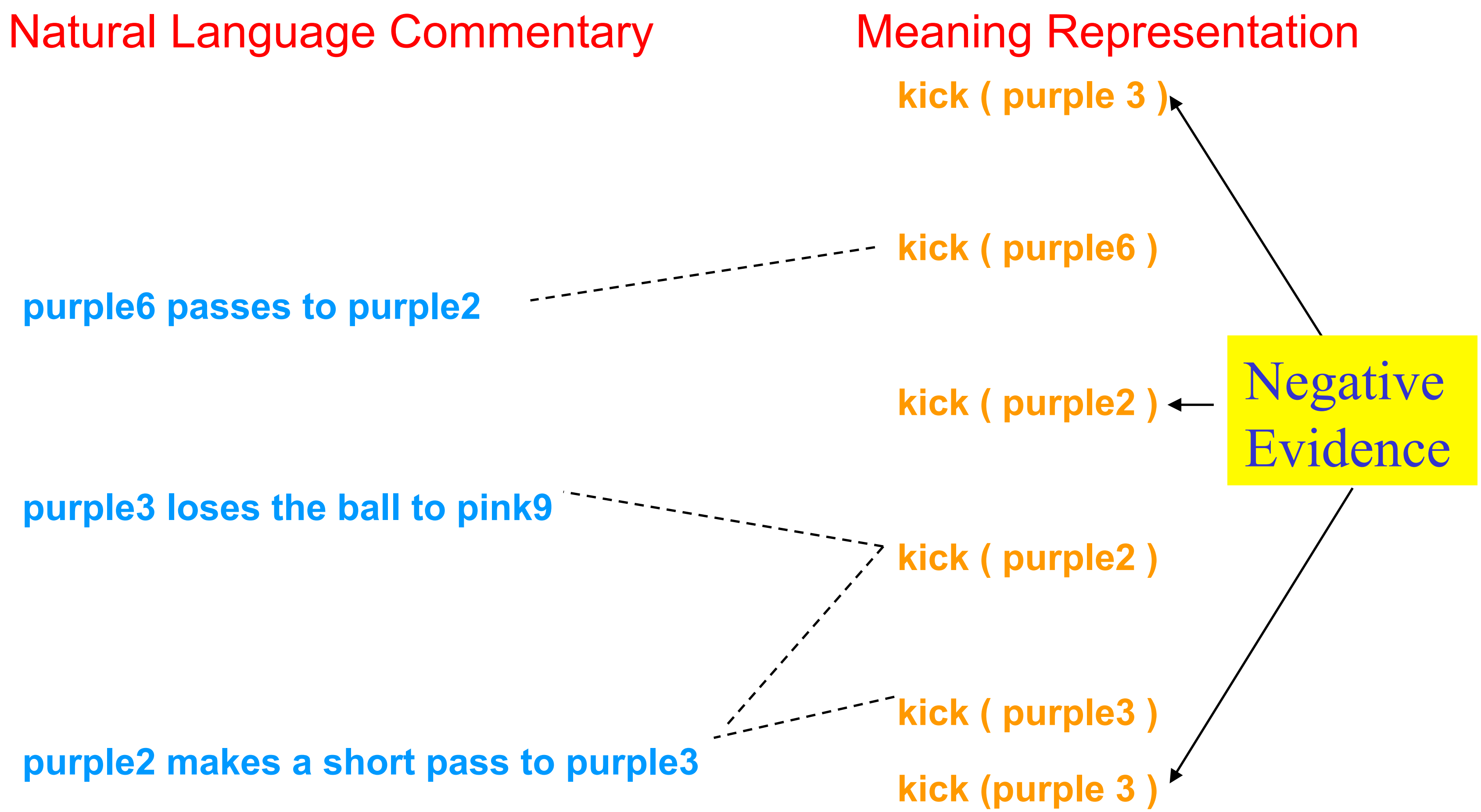

# Strategic Generation Performance

- Evaluate how well the system can predict which events a human comments on
- Metric:
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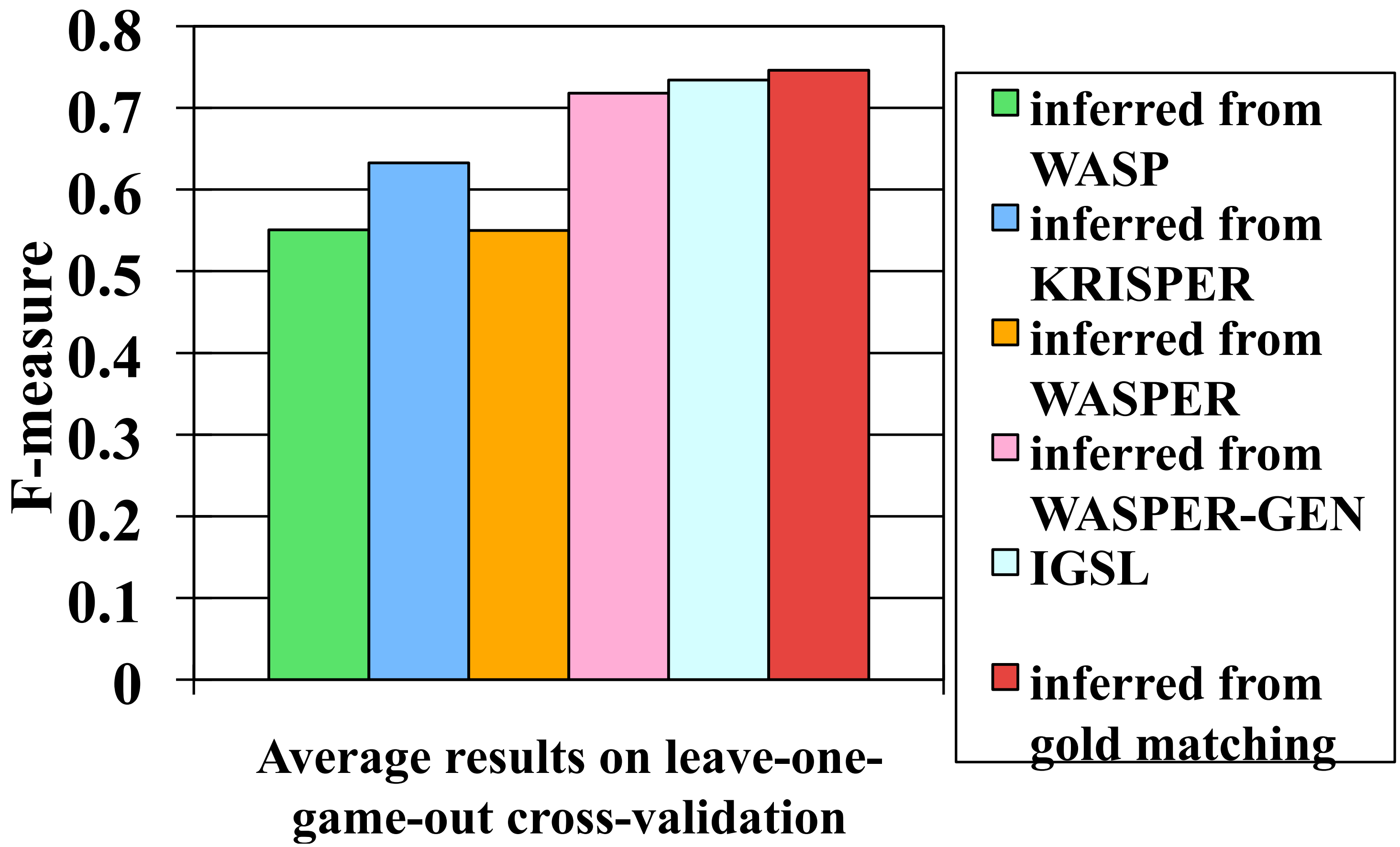
# Strategic Generation Results



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