

Qualitative spatial reasoning for soccer pass prediction

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2. Data
3. Challenges
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Qualitative spatial reasoning

Suppose we have **spatiotemporal data**.

Hypothesis:

It is possible to learn a meaningful qualitative model over the data

How to test this?

Soccer pass prediction based on spatiotemporal player data:

“Can we predict to whom a player is going to give a pass?”

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Soccer match data

- During a soccer match, three, different types of data are available

1. Spatiotemporal data

player_ID	time	X	Y	events_half
345555	18500	-3455	300	1
356778	18500	220	-1567	1
245777	18500	10	-908	2

2. Event data

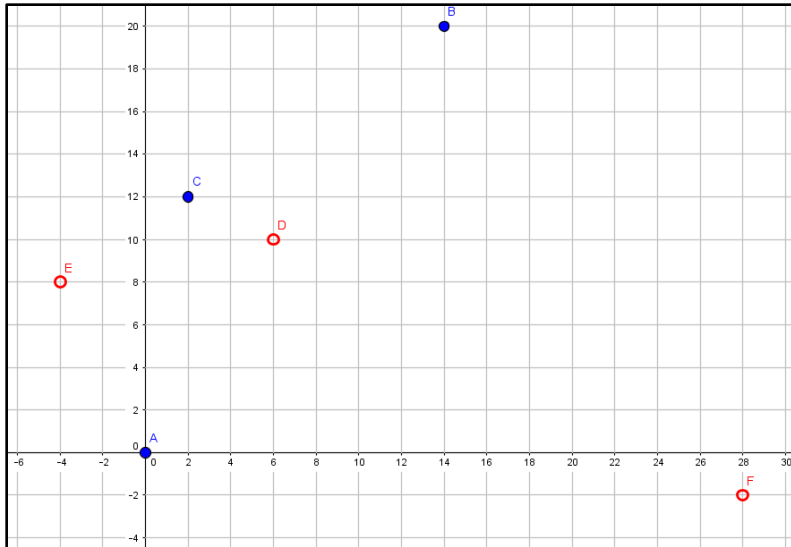
player_ID	time	event	...	events_half
345555	18500	pass	...	1
356778	18500	reception	...	1
245777	22300	pass	...	2

3. Background knowledge

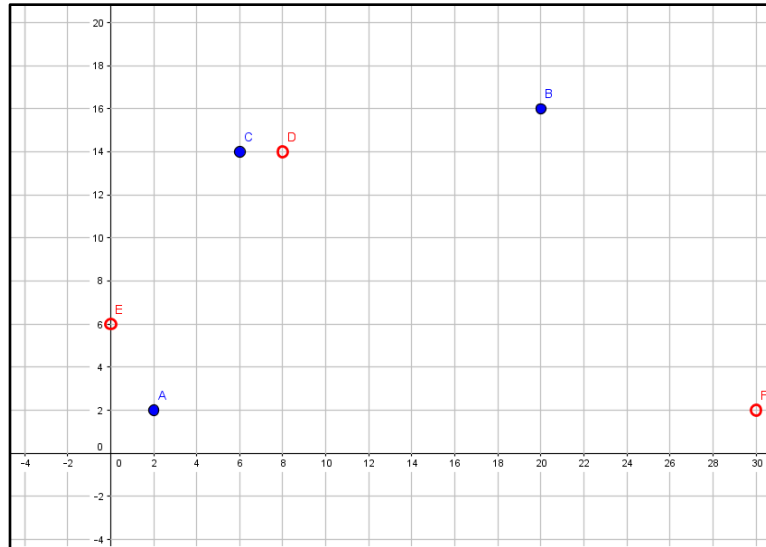
player_ID	team	position	...	name
345555	A	midfield	...	Jack
356778	A	defender	...	Stephen
245777	B	attack	...	John

Pass event

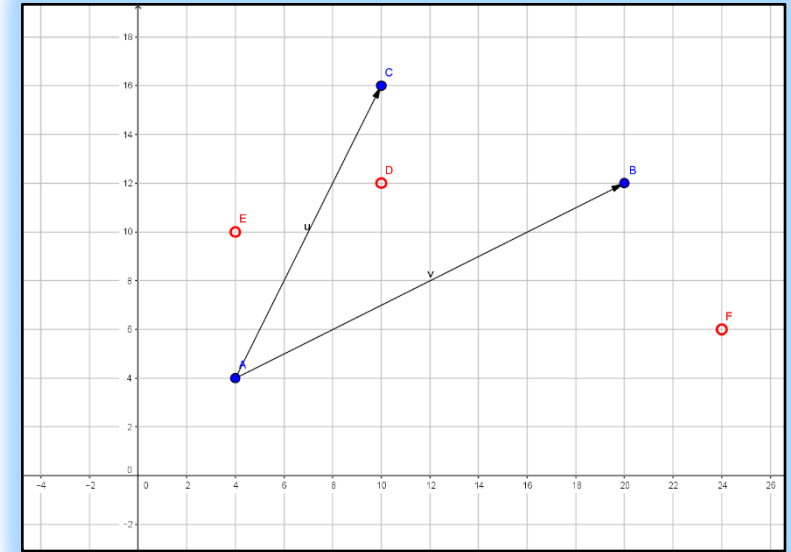
t-2 (no pass)



t-1 (no pass)



t (pass)



	A	B	C	D	E	F
X	0	14	2	6	-4	28
Y	0	20	12	10	8	-2

	A	B	C	D	E	F
X	2	20	6	8	0	30
Y	2	16	14	14	6	2

	A	B	C	D	E	F
X	4	20	10	10	4	24
Y	4	12	16	12	10	6

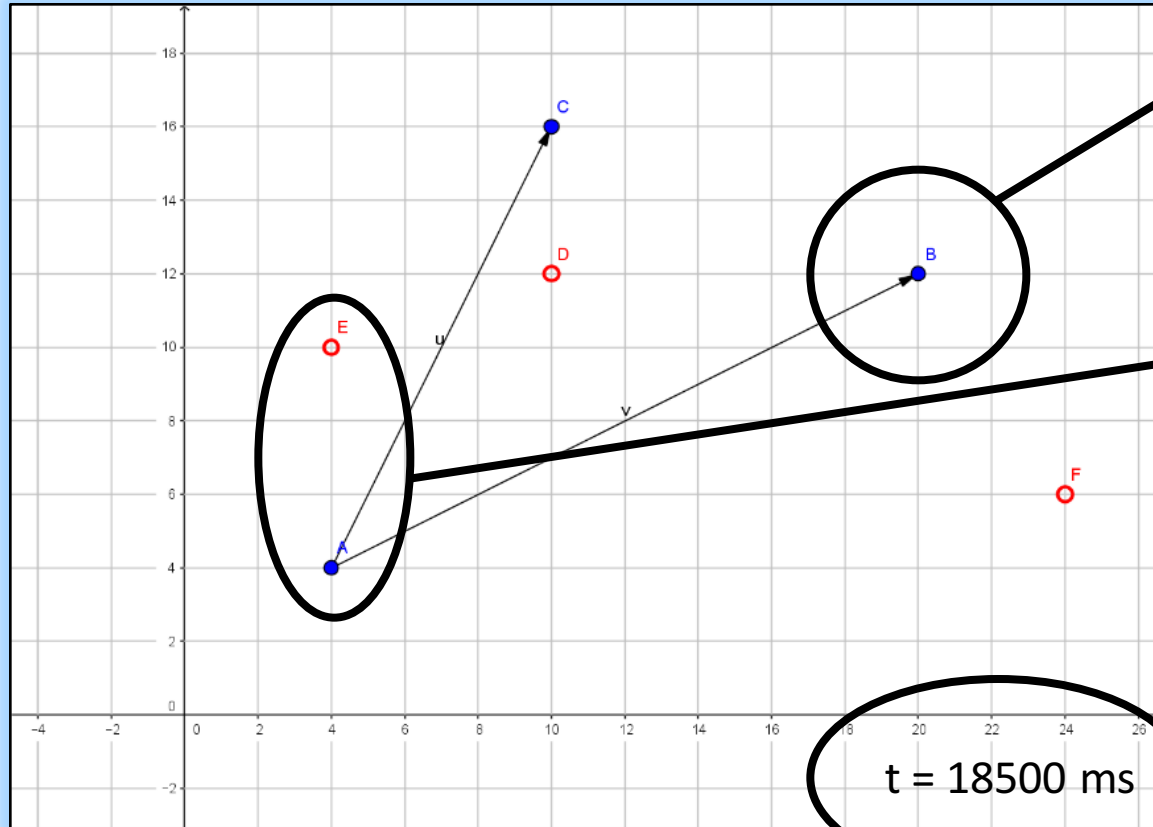
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Quantitative reasoning...

- Difficult to learn directly over **exact spatiotemporal data**
 - No single pass will be given in the same exact locations
 - Size of the pitch will change between stadiums = different reference framework
 - Prone to inaccurate measurements
- Soccer data contain **relations and complex interactions**
 - players base their decisions on how they are positioned with respect to other players...
 - ...and how these players interact
- Soccer data are inherently **dynamic**
 - passing decisions are made in the moments leading up to the pass

Challenges: pass event



The exact position will never be the same

How can we express relations between players?

player(A, E, north)

player(B, free)

What about the moments leading up to the pass?

... or qualitative reasoning?

- Difficult to learn directly over **exact spatiotemporal data**
 - generalization
- Soccer data contain **relations and complex interactions**
 - framework to **express relations + combine different types of knowledge**
- Soccer data are inherently **dynamic**
 - encode **information over time**

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Methodology

Goal: learn a **predictive model** from data

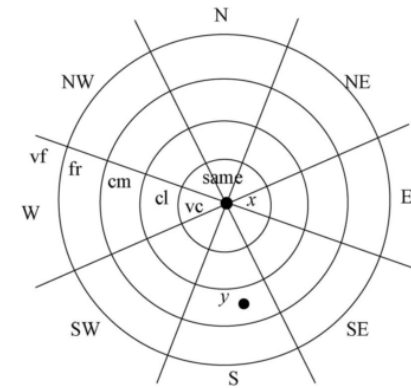
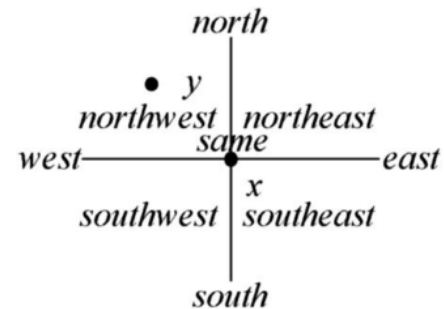
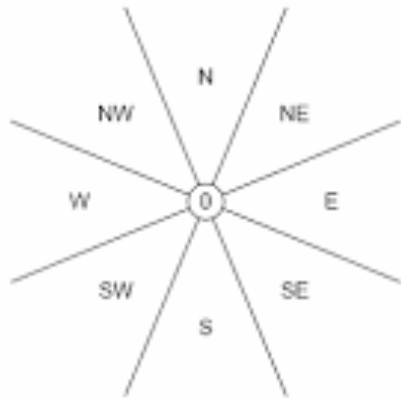
- 1. Data:** consider each pass event as a labelled training example
 - Positive example = player that receives the pass
 - Negative example = other teammates on the field at that time
- 2. Features:** extract features that qualitatively describe the pass event
- 3. Model:** Learn a prediction model using features and background info
- 4. Predict:** Construct ranking of who is most likely to receive a pass in unseen example

Extract qualitative features

- **Qualitative spatial reasoning (QSR)** is an umbrella term for a number of formalisms (calculi) that define how entities in a 2D or 3D space behave
 - QSR's describe relations between objects in a qualitative way
 - Relations are mostly binary, yet can have higher degrees
 - Numerous categories of QSR's exist:
 - Mereotopology
 - Direction
 - Distance
 - Moving objects
 - Shape
 - ...
- These are interesting for the problem at hand

Qualitative Spatial Representations

- **Cone-shaped direction calculus OR projection-based direction calculus**
 - 8 binary relations – JEPD (*jointly exhaustive pairwise disjoint*)
 - These basic calculi can be extended with distance information
 - Represents static relations

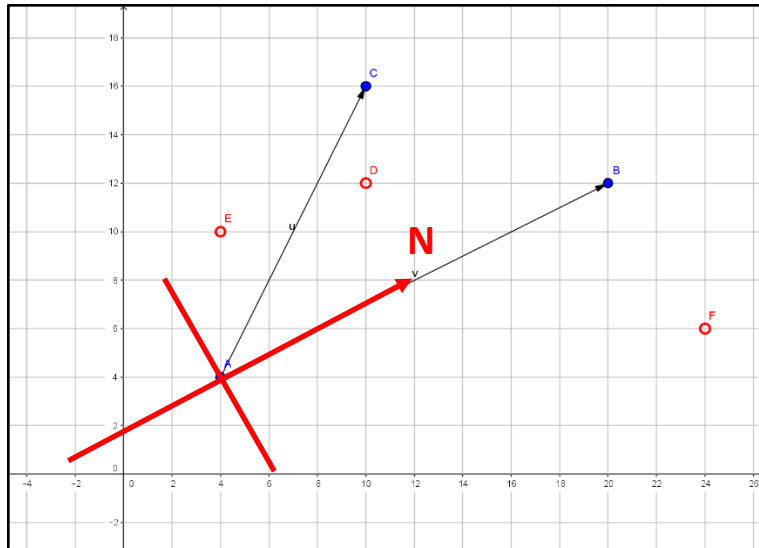


Directional information

Directional and distance information

Qualitative Spatial Representations

- **Cone-shaped direction calculus OR projection-based direction calculus**
 - Use the *receiver* and *passer* as points of reference
 - Capture players' position with regards to passer and receiver



	A	B	C	D	E	F
A		N	NW	NW	W	NE
B	S		W	SW	SW	E
C	SE	E		E	S	E
D	SE	NE	W		S	E
E	E	NE	N	N		NE
F	SW	W	W	W	SW	



passer



actual receiver

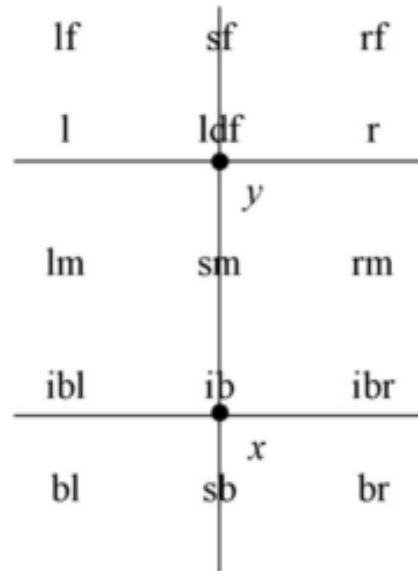
No pass (from A to C):

	NE	N	N	N	NE
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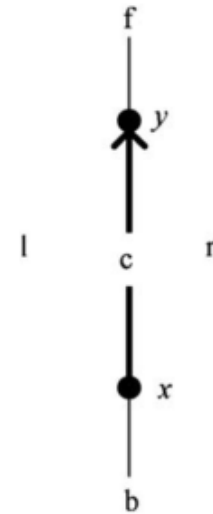
Qualitative Spatial Representations

- **Double-cross calculus OR LR calculus**

- 15 *ternary* JEPD relations
- Represents static relations



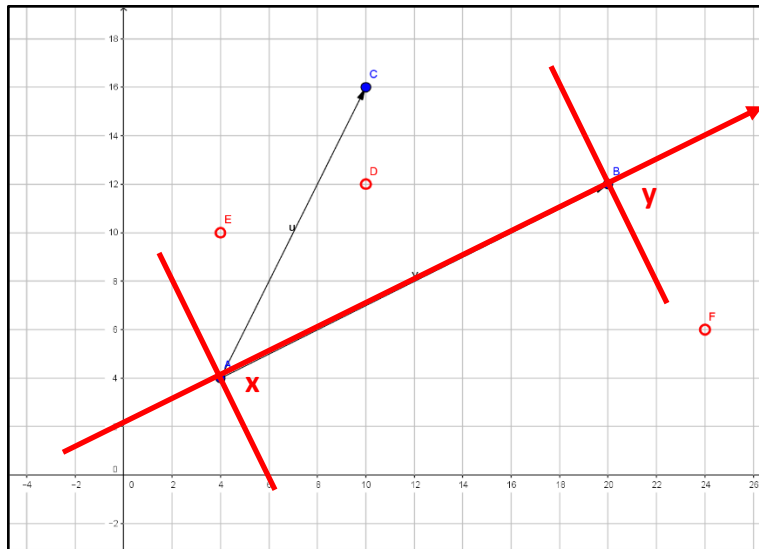
Double-cross



LR calculus

Qualitative Spatial Representations

- **Double-cross calculus OR LR calculus**
 - Use the *passline* as a point of reference
 - Captures players' position with regards to the passline

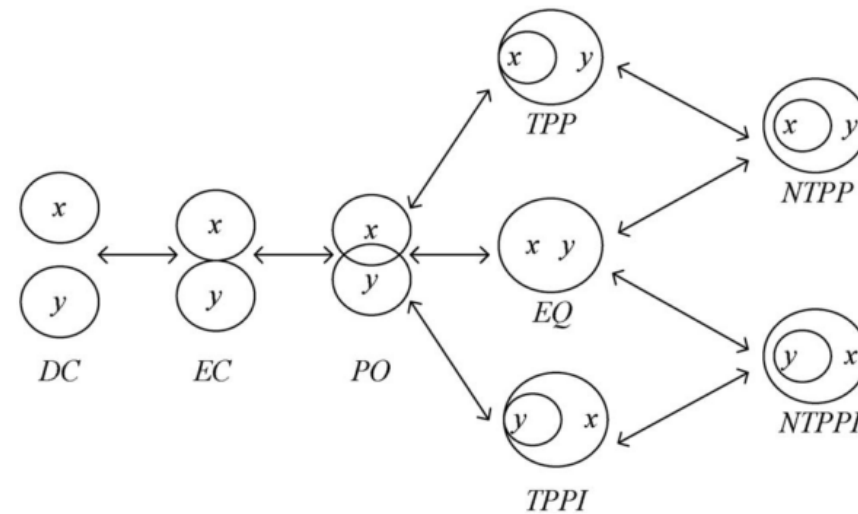


	A	B	C	D	E	F
ref	ib	rf	ldf	rm	lm	rm
ref	ib	ldf	lm	lm	lm	rf

Qualitative Spatial Representations

- **Region connected calculus (RCC8/RCC5) calculus**

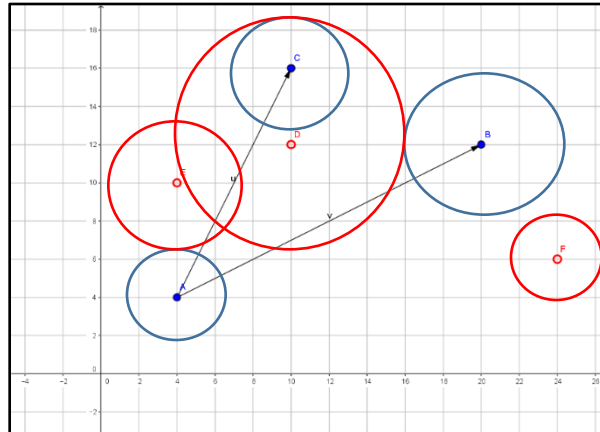
- 8 binary JEPD relations
- Expresses relations between regions
- Represents static or dynamic relations



Qualitative Spatial Representations

- Region connected calculus (RCC8/RCC5) calculus

Simple model:

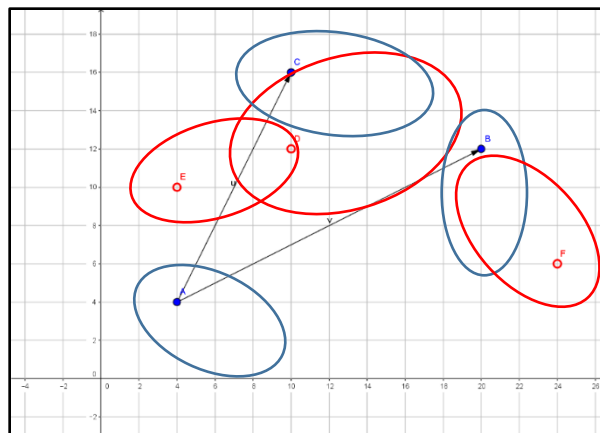


	A	B	C	D	E	F
A		DC	DC	DC	EC	DC
B	DC		DC	EC	DC	DC
C	DC	DC		TPP	DC	DC
D	DC	EC	TPI		PO	DC
E	EC	DC	DC	PO		DC
F	DC	DC	DC	DC	DC	

← passer

← actual receiver

Complex model:



	A	B	C	D	E	F
A		DC	DC	DC	DC	DC
B	DC		DC	EC	DC	PO
C	DC	DC		PO	DC	DC
D	DC	EC	PO		PO	DC
E	DC	DC	DC	PO		DC
F	DC	PO	DC	DC	DC	

← passer

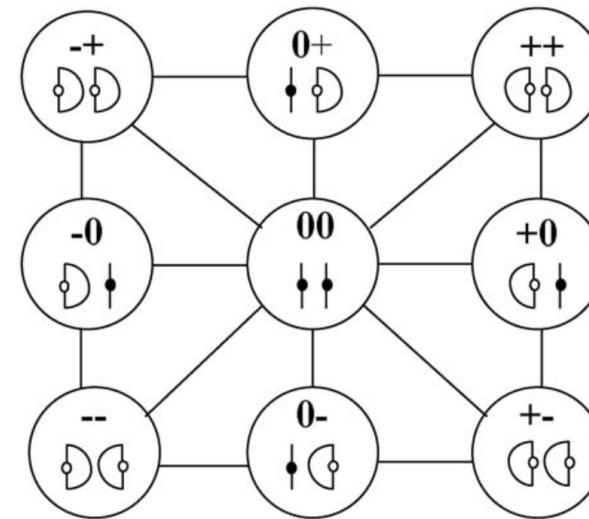
← actual receiver

Qualitative Spatial Representations

- **Dipole calculus OR qualitative trajectory calculus**
 - Captures movement information
 - Both *spatial* and *temporal* information

$\uparrow\uparrow$ $x rrr y$	$\uparrow\leftarrow$ $x rrl y$	$\uparrow\rightarrow$ $x rlr y$	$\uparrow\uparrow$ $x rll y$	$\leftarrow\uparrow$ $x rlr y$	$\rightarrow\uparrow$ $x rlr y$	$\rightarrow\uparrow$ $x rll y$	$\rightarrow\uparrow$ $x lrr y$
$\rightarrow\uparrow$ $x lrl y$	$\rightarrow\uparrow$ $x lrl y$	$\uparrow\uparrow$ $x llr y$	$\rightarrow\uparrow$ $x llr y$	$\leftarrow\uparrow$ $x llr y$	$\downarrow\uparrow$ $x lll y$	$\leftarrow\uparrow$ $x ells y$	$\uparrow\rightarrow$ $x errs y$
$\rightarrow\uparrow$ $x lere y$	$\uparrow\leftarrow$ $x rele y$	$\leftarrow\uparrow$ $x slsr y$	$\uparrow\rightarrow$ $x srsl y$	$\rightarrow\uparrow$ $x lsel y$	$\uparrow\leftarrow$ $x rser y$	\uparrow $x sese y$	$\uparrow\downarrow$ $x eses y$

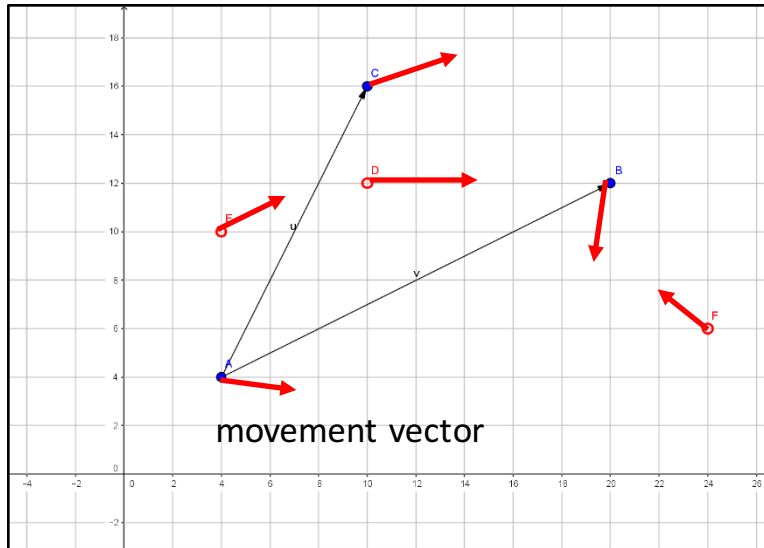
Dipole calculus



Qualitative trajectory calculus

Qualitative Spatial Representations

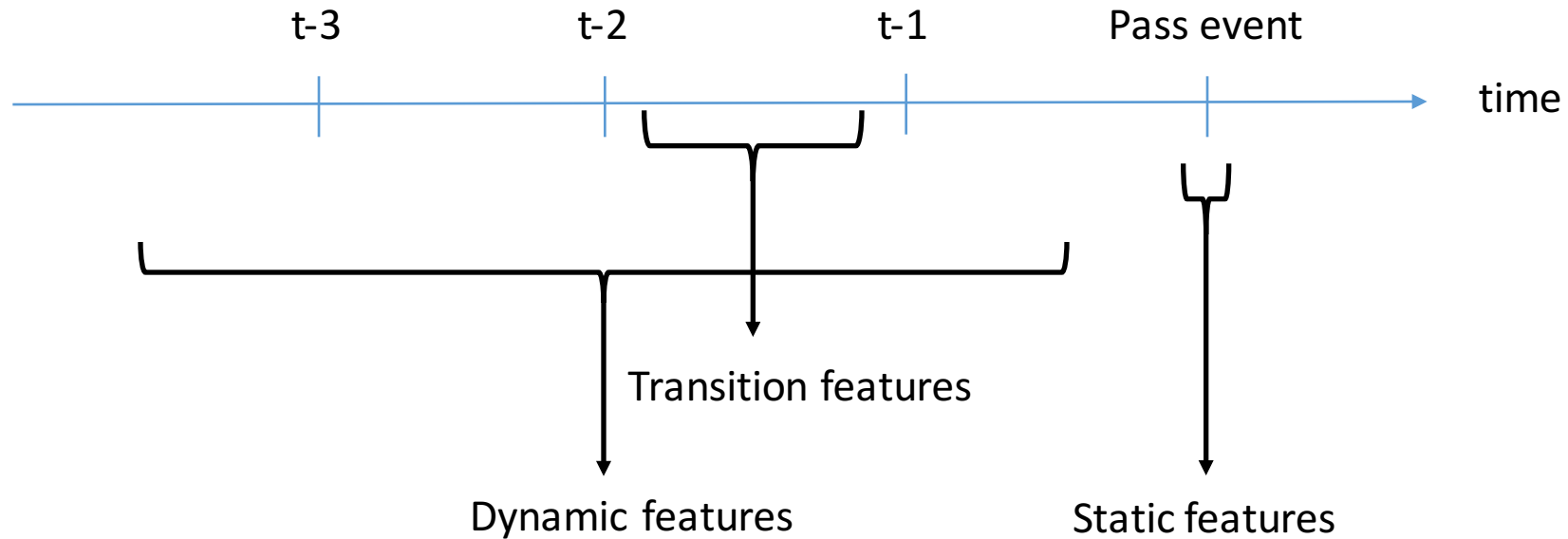
- **Dipole calculus OR qualitative trajectory calculus**
 - Captures movement information
 - Both *spatial* and *temporal* information



	A	B	C	D	E	F
A		<i>llrl</i>	<i>llrr</i>	<i>Llrr</i>	<i>llrr</i>	<i>llll</i>
B	-		<i>errs</i>	<i>rlll</i>	<i>errs</i>	<i>rele</i>
C	-	-		<i>rrrr</i>	<i>rrrr</i>	<i>rrrl</i>
D	-	-	-		<i>llrr</i>	<i>Llll</i>
E	-	-	-	-		<i>rele</i>
F	-	-	-	-	-	

← **passer**
← *receiver*

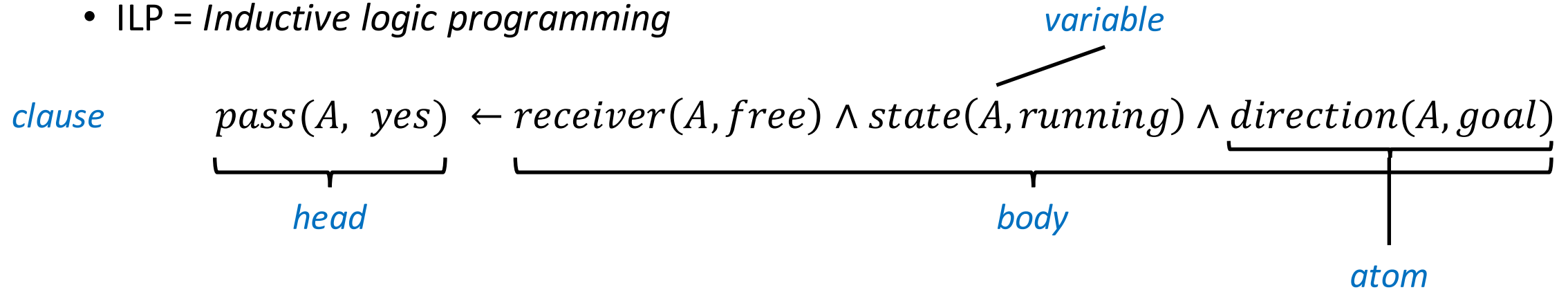
Capture the dynamics



- **Static features** only capture information at the moment of the pass
- **Dynamic features** capture information in moments leading up to the pass
- **Transition features** describe the transition between moments

Learn a prediction model with ILP

- ILP = *Inductive logic programming*



- ILP allows to encode knowledge with *logic programs*
- The above rule states

“If player A is free and running towards the goal, I will pass to him”

- Ideal to encode the qualitative relations from the QSR’s
- We can express background knowledge in the dataset

Learn a prediction model

- ILP algorithm 1: **TILDE**
 - Learns a decision tree
 - Divide-and-conquer
 - Transform tree to rule-set
 - PROBLEM: **not robust to skewed data distribution & increasing amount of features**
 - ILP algorithm 2: **ALEPH**
 - Separate-and-conquer
 - Learns theory (= set of rules) that classifies examples
 - Starts from bottom-clauses that are refined and selected according to criteria
 - More robust to skewed distribution & increasing amount of features
- We can use the learned rules that encode *pass* or *no pass* to predict unseen cases


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Evaluation metric

- Best evaluation metric is a **ranking** between players
 - Award higher score if the model ranks the actual receiver higher
 - Example

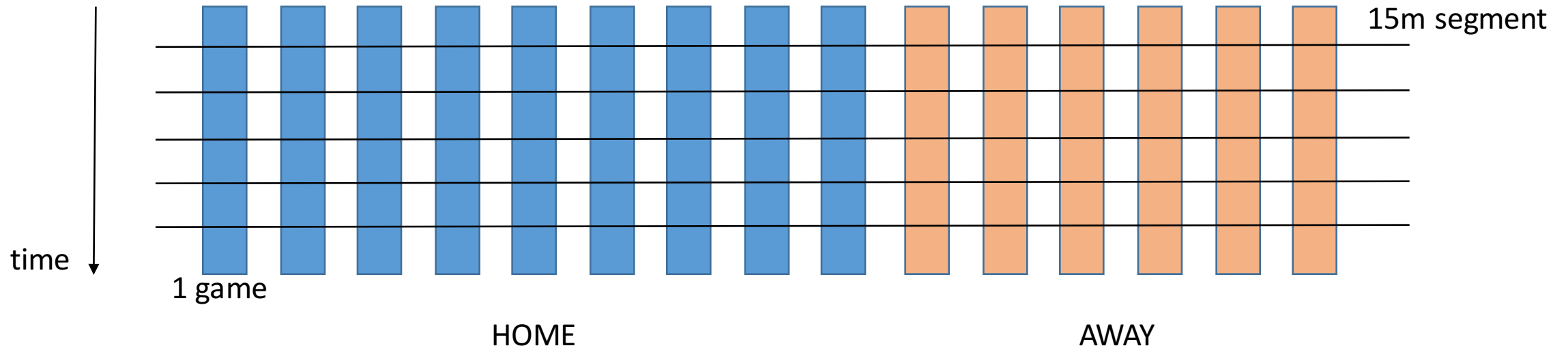
Example	A	B	C	D	E	...	J
1	1	4	6	3	10		2
2	4	2	1	6	8		5

 = actual receiver

- **Accuracy** is only 0.5
 - **Mean reciprocal rank (MRR)** is 0.75
- Accuracy is a lower bound of the MRR:

$$\text{Accuracy} = \frac{\sum_{i=1}^n x_i}{n} \leq \text{MRR} = \frac{\sum_{i=1}^n \frac{1}{x_i}}{n}$$

Train and test data



- 14 games are available: 9 home and 6 away
- This allows us to construct some interesting [sports-related hypotheses](#)

Experimental hypotheses

- **Base hypothesis:**

- Is the qualitative approach better than the quantitative at learning a meaningful model?

- **Sports-related questions:**

- Is there a difference in the passing behaviour of a team at home and away?
- Is there a decrease in performance throughout the game, altering passing behaviour?
- Is passing behaviour team specific?

Results

1. Is the qualitative approach better than the quantitative at learning a meaningful model?

		MRR	top-1	top-2	top-3	Rules
Quant.	Non-rel.	0.11	0.84	0.93	0.93	8
	Rel.	0.24	10.82	18.16	21.76	524
Qual.	Static	0.39	25.49	36.33	41.22	582
	Dynamic	0.32	15.48	26.49	34.75	687
	Transition	0.33	17.48	29.24	35.00	681
	Combined	0.42	27.87	41.59	46.70	555

MRR = mean reciprocal rank

top-* = percentage of times the actual receiver is ranked accordingly by the learned model

Rules = number of logic rules in the learned theory

- A non-relational quantitative model cannot learn a meaningful model
- The qualitative approach is clearly better than a quantitative model
- The best model considers all information in the moments leading up to the pass

Results

1. Is there a difference in the **passing behaviour of a team at home and away**?
→ a home-trained model performs worse on away data and vice versa
2. Is there a **decrease in performance throughout the game**, altering passing behaviour?
→ a model performs better when it is applied to the same moment of the game it is trained on
3. Is passing behaviour **team specific**?
→ the model performs better when trained on a specific team and applied to that team

		MRR	top-1	top-2	top-3	Rules
1	{ Train home - test home	0.42	27.87	41.59	46.70	555
	{ Train home - test away	0.37	21.56	35.25	40.58	712
2	{ Train 1st half - test 1st half	0.42	27.87	41.59	46.70	555
	{ Train 1st half - test 2nd half	0.38	27.15	31.95	36.03	620
3	{ Train 1 team - test multiple	0.28	13.15	22.44	30.00	591
	{ Train multiple - test multiple	0.37	23.71	35.05	40.33	381

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Conclusion

- Main messages:
 - qualitative, relational approach learns meaningful models
 - dynamics of the game are important
- Questions?