# USING MACHINE LEARNING TO ASSESS PLAYER QUALITY IN TEAM SPORTS

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# Assessing players a worth-while challenge in team sports

1. Is she worth a large contract ?
   – Who’s the best player in the NHL and are they undervalued ?
2. How do we find a (cheaper) replacement ?
   – Replacing CR7, for example.
3. Do they perform well in particular situations?
   – Does Neymar make good decisions under pressure ?
4. Can we find hidden gems ?
   – Who’s not in the top-10 but should be ?

# How to assess a player ?

1. Does things that help the team, avoids things that hurt it
   - Scoring helps
   - Preventing to score helps
   - Put teammates in position to score helps
   - Losing the ball doesn't
2. Standard human way of assessment : discrete actions
   - Goal
   - Assist
   - Block

**Harder for more diffuse actions :**
- **Setting a screen**
- **Help defense**

# How to assess the quality of an action

- Human experts
  - Biased
  - Slow (90 mins+)
  - Not that many experts around
- Hard to do for actions far in the past
  - The pass directly before a goal is clear
  - The screen 10 seconds before, though ?

# Assessment via machine learning

- Learn a model that assigns (numerical) values to actions
  - Ground truth : based on expert assessments
  - Or on back-propagation of positive/negative outcomes
- Score all of a player's actions
  - Even the ones that occurred long before a score
  - Or the ones that occurred off the ball
- Calculate (category-specific) averages
  - Some player are better passers/defenders etc

# High-level plan

- Soccer :
  - « Not all passes are created equal », Power et al. KDD ‘17
  - « Actions speak louder than goals », Decroos et al. KDD ‘19
  - « Choke or shine », Bransen et al. MSSAC ‘19
- Basketball :
  - « Deephoops: Evaluating micro-actions in basketball using deep feature representations of spatio-temporal data », Sicilia et al. KDD ‘19
  - « Bhostgusters: Realtime interactive play sketching with synthesized NBA defenses », Seidl et al. MSSAC ‘18
- Ice hockey :
  - « Deep Reinforcement Learning in Ice Hockey for Context-Aware Player Evaluation », Liu & Schulte IJCAI ‘18

# Not all passes are created equal

- Consider passes' risk and reward
- Event data + player tracking data
  - Derived features
  - Tactical features
  - Formation features
- **Logistic regression** to learn risk
  - Wanted interpretability
- Pass reward : probability of score within 10 secs
  - Also logistic regression
- Formations
  - **Clustering**

# Actions speak louder than goals

- Assess all actions, not just passes
- Event stream data
  - SPADL, derived + contextual
- Valuing Actions by Estimating Probabilities (VAEP)
  - Change in probability for scoring/conceding in « near future »
- **CatBoost** to learn probabilities for given game state
  - Form of gradient boosted decision trees

# Choke or shine

- Do players make good choices/execute well under pressure ?
- Pre-game (mental) pressure, in-game (mental) pressure
- Pre-game :
  - Team ambition : **k-means clustering**
  - Pair-wise rankings of games : **Gradient-boosted tree** to learn pressure
- In-game :
  - Based on state t, predict goals until end of match
  - **Auto-Differentiation Variational Inference** algo for learning
- « Actions speak louder than goals » values
- **Gradient-boosted trees** learn success/failure of actions

# Deephoops

- « Micro-actions » : screens, cuts etc
- Player-tracking data
  - Sliding window instead of full possessions
- Labeled windows → expected points value → change in EPV
- **Long short-term memory** (LSTM) model to predict
  - Complex architecture
- Combined w/learned player **embedding**
- « What if » assessments

# Bhostgusters

- How would the defending team respond ?
- Player tracking data
  - + game context data
- Learn **typical** player trajectories by **LSTM** model
- Evaluate observed offensive possessions
  - Actions can be switched out for « what if » scenarios
- Sketch hypothetical ones
  - → routes for players, i.e. succession of actions : pass, dribble, move etc

# Deep Reinforcement Learning in Ice Hockey for Context-Aware Player Evaluation

- How good is the action a player performs in a particular situation ?
- Event data
  - + derived features
- Split up into goal-scoring episodes
  - Subdivided via possession changes
- Learn Q-function to assess actions
- **LSTM network** as learner
- Changes in Q value used to assess player

# Let’s talk data – what is event stream data ?

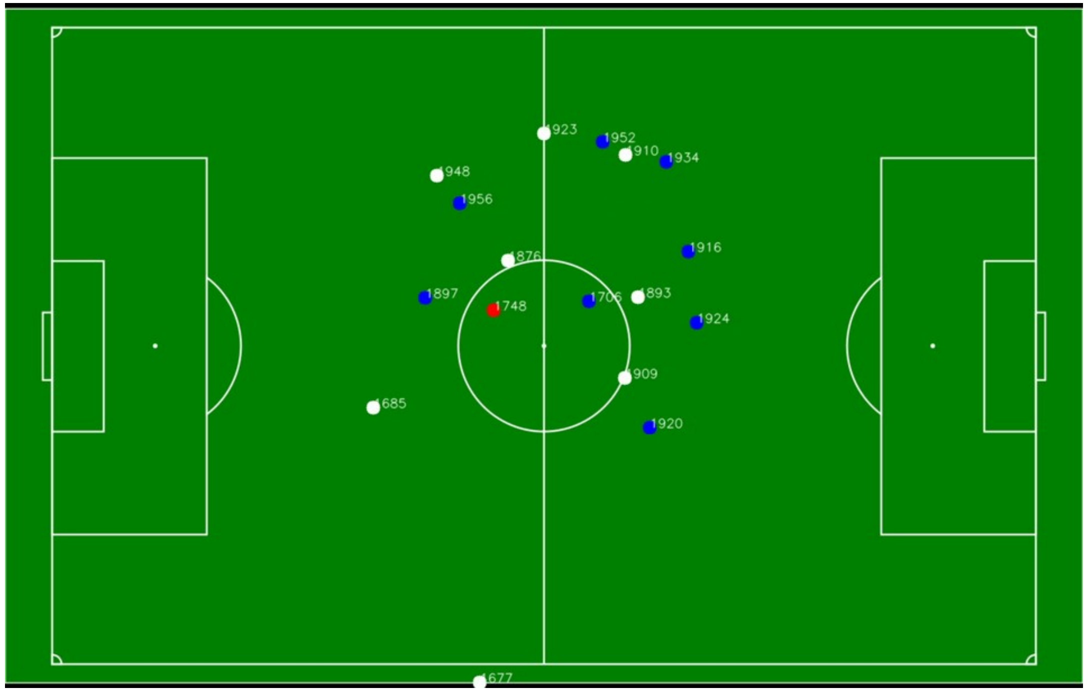
1. Something discrete happens
   - Pass, tackle, block, turnover etc
   - Events = actions
2. Annotated with
   - x, y coordinates (origin, arrival)
   - Involved player(s)
   - Time stamp (beginning, end)
3. Derived from annotators’ work
   - Watch the video, use particular software
   - Some work on automatizing things
4. Irregular intervals

- « Simple pass »
  - PlayerID : 25413
  - x:49, y:49
  - x:78, y:31
  - EventSec :2.7586489999999912
- « High pass »
  - PlayerID  : 370224
  - x:78, y:31
  - x:75,y :51
  - EventSec :4.946850000000012

**Pappalardo, Luca; Massucco, Emanuele (2019): Soccer match event dataset. figshare. Collection. https://doi.org/10.6084/m9.figshare.c.4415000.v5**

# Let’s talk data – what is (player) tracking data ?

1. Where are the players ?
   – x, y coordinates
2. Where’s the ball ?
   – x, y, z coordinates
3. Derived from camera images + entity recognition
   – Team shirt colors help
4. Regular intervals
   – Typically 20-25 Htz



# Let’s talk data

- Why events data ?
  - Because events/actions are what makes the game go ‘round
- Why not only events data ?
  - Because a pass w/o close-by defenders is a completely different thing
- Why tracking data ?
  - Because it gives a complete picture
- Why not only tracking data ?
  - Because positions don’t tell anything about actions

# Not all passes are created equal : Objectively Measuring the Risk and Reward of Passes in Soccer from Tracking Data

- Pass the **most** often occurring action in soccer
- Some easy ways of assessing passes :
  - Success/failure
  - Assist
- Assist = great pass
- Successful pass = good pass ?
- Failed pass = bad pass ?

| | High risk | Low risk |
|---|---|---|
| **High reward** | ? | Good pass |
| **Low reward** | Bad pass | ? |

# Not all passes : data (STATS Inc paper)

- 726 EPL matches
- Player positions sampled at 10hz
- Event data, e.g. pass, tackle, shot :
  - x, y ball position, time stamp
  - Player in position
  - Player identity of opposing player for duels
- 571,287 passes, of which 468,265 successful (84.35%)

**Sideways, backwards more successful**
**Closer to goal less successful**
**Longer less successful**

**Imbalance problematic**

# Pass risk

- Probability that a player completes a pass he plays
- Derived features :
  - Speed of passer and receiver
  - Speed/distance of nearest defenders
  - Nearest defender angle to passing line
  - First time pass ?
  - Time from regaining possession
  - Most likely intended receiver : distance/min distance * angle/min angle
- Risk learned via **logistic regression**

Data transformation

# Tactical + formation features

- Build-up, counter-attack, unstructured play
  - Expert assessment
- Formation clustering
  - Polar coordinates of all players w.r.t. goal
  - Polar coordinates of defenders w.r.t. passer/receiver
- **K-means** to identify high-, medium-, low-block (defensive)

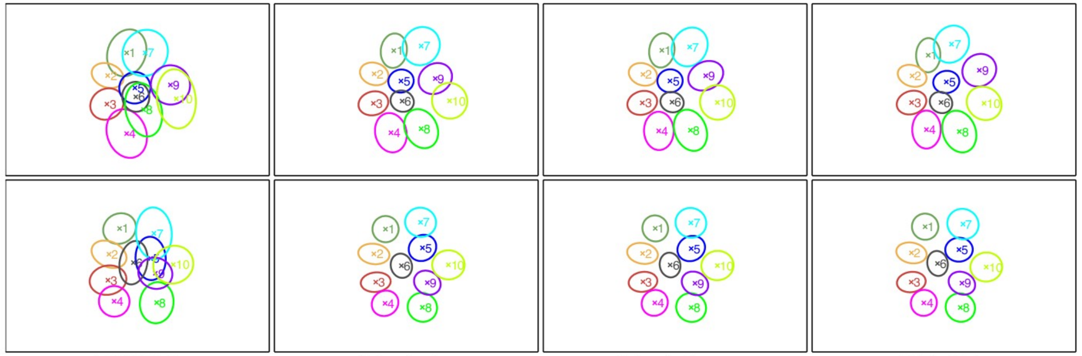
**Data transformation/ augmentation**

# Formation clustering

Large-Scale Analysis of Soccer Matches using Spatiotemporal Tracking Data, Bialkowski et al. ICDM '14

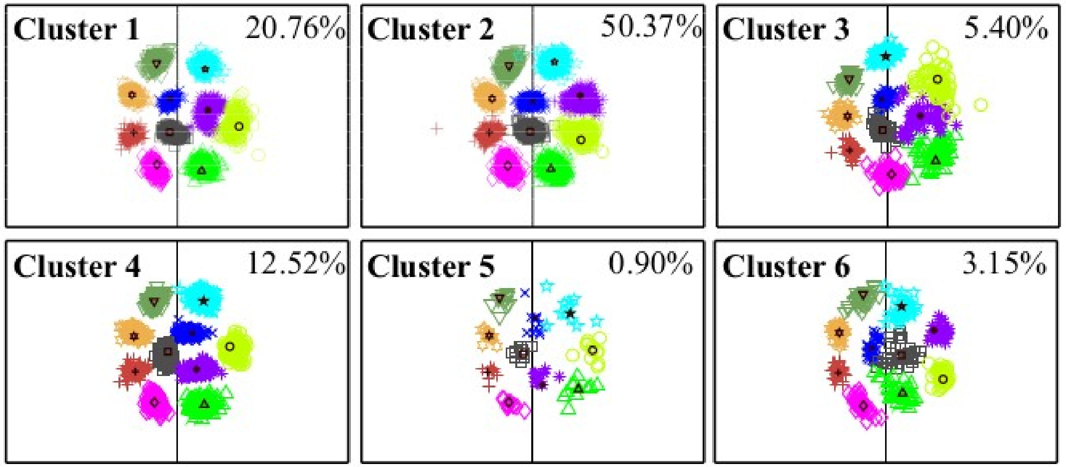


- Group similar data points, separate dissimilar ones
  - **Unsupervised** problem
- Team formation = set of roles
- One team per frame
- Normalized → zero mean for all tracking data
- Cluster « role positions » until convergence → formation
  - **EM algorithm**



(a) Initial Roles (b) Iteration 1 (c) Iteration 2 ... (d) Final Roles

- Results in 1411 formations
  - Cluster with **HAC** using Earth Mover's distance → 6 clusters

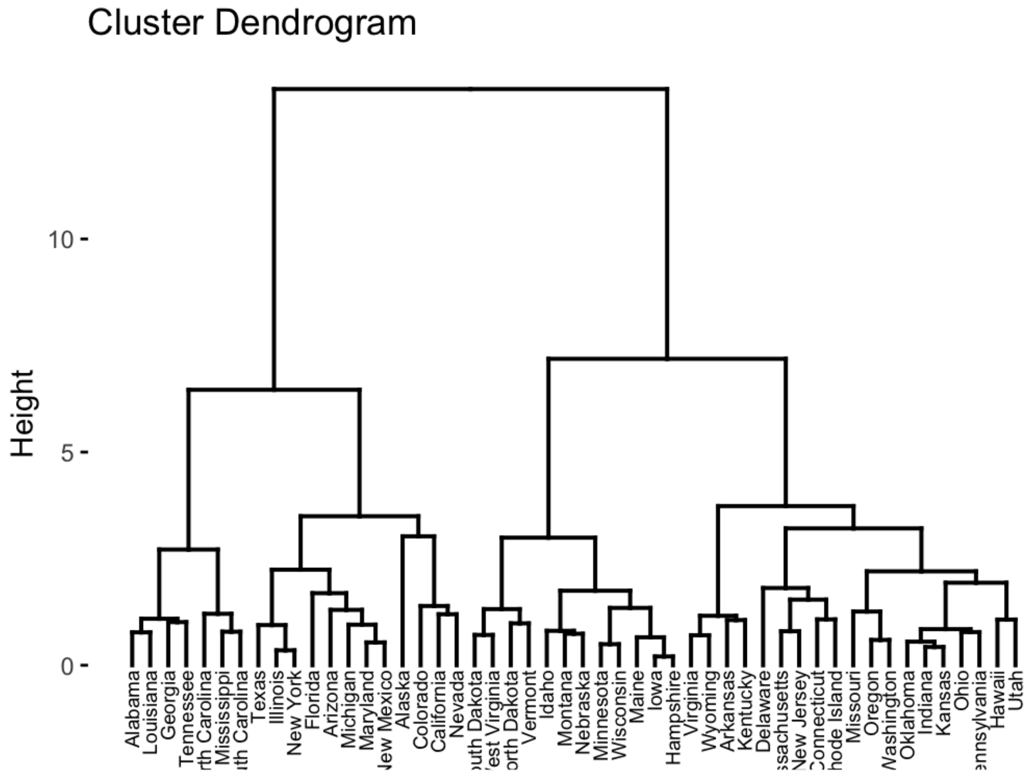


# The ML element : EM

- Expectation Maximization algorithm
- Generative model :
  - Clusters represented as mix of Gaussians (means, covariance matrix)
  - Probability for each Gaussian
  - All of which are learned
- Alternating :
  - For each point, calculate probability for belonging to different Gaussians
  - Assign to most likely one
  - Update Gaussians' parameters
  - Repeat

# The ML element : HAC

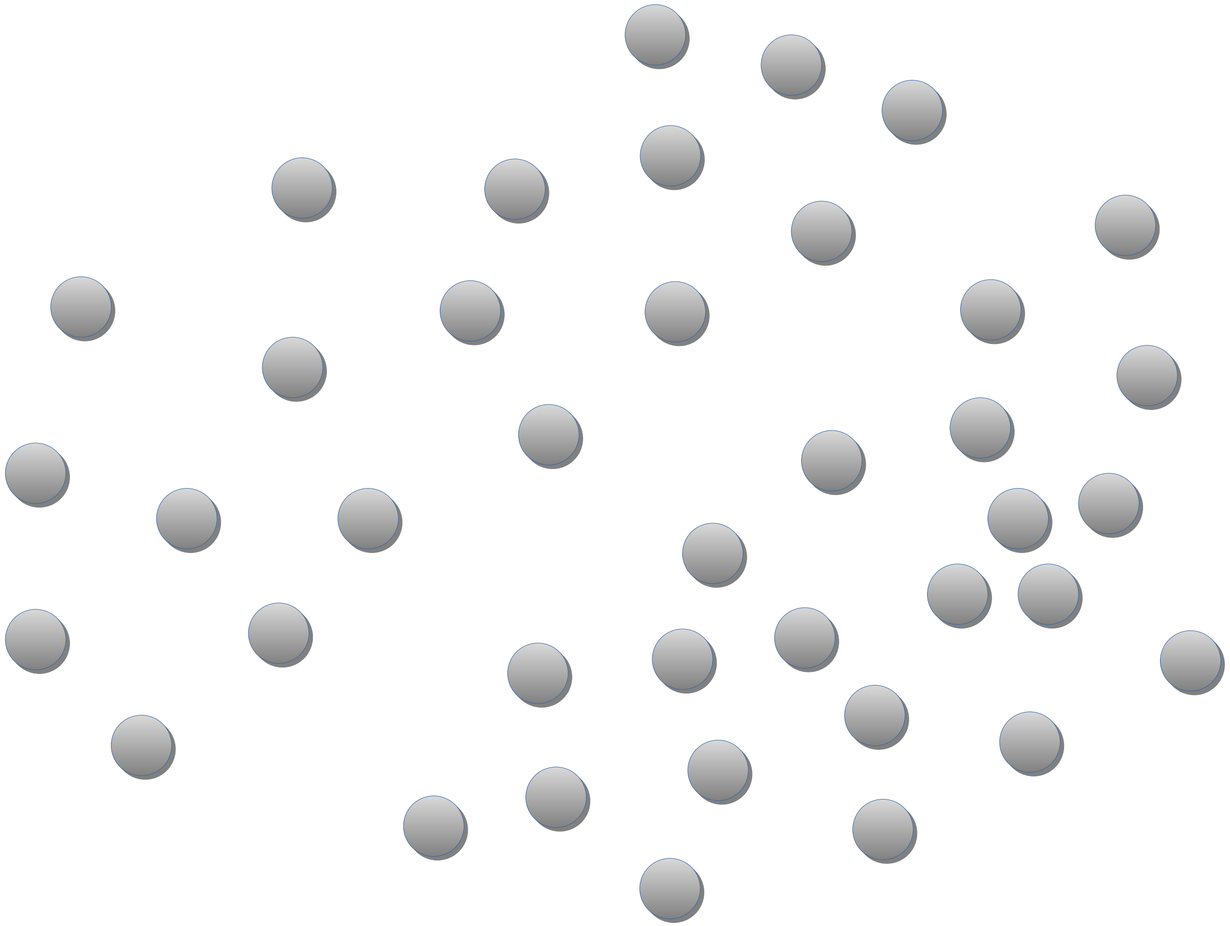
- Hierarchical agglomerative clustering
- In the beginning, each data point its own cluster
- Merge the two closest ones
- Until only a single cluster left
- The « tree » structure is learned



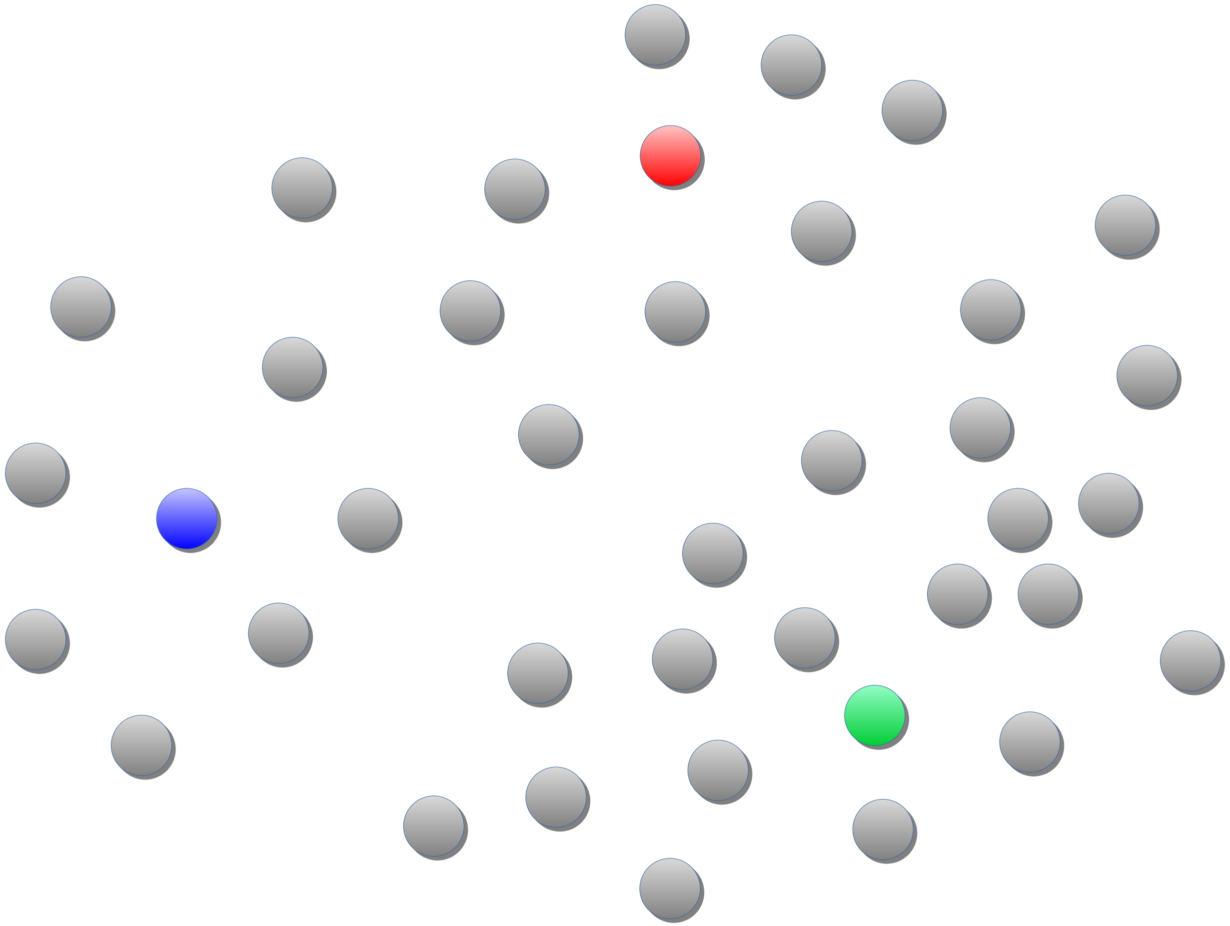
# The ML element : k-means clustering

- Cluster represented as « centroids » - mathematical middle of a « cloud » of points
  - Which are learned
- Pick starting centroids at random
- Assign each point to most similar centroid
- Recalculate centroids (average over all cluster points)
- Repeat
- Minimizes sum of intra-cluster distances

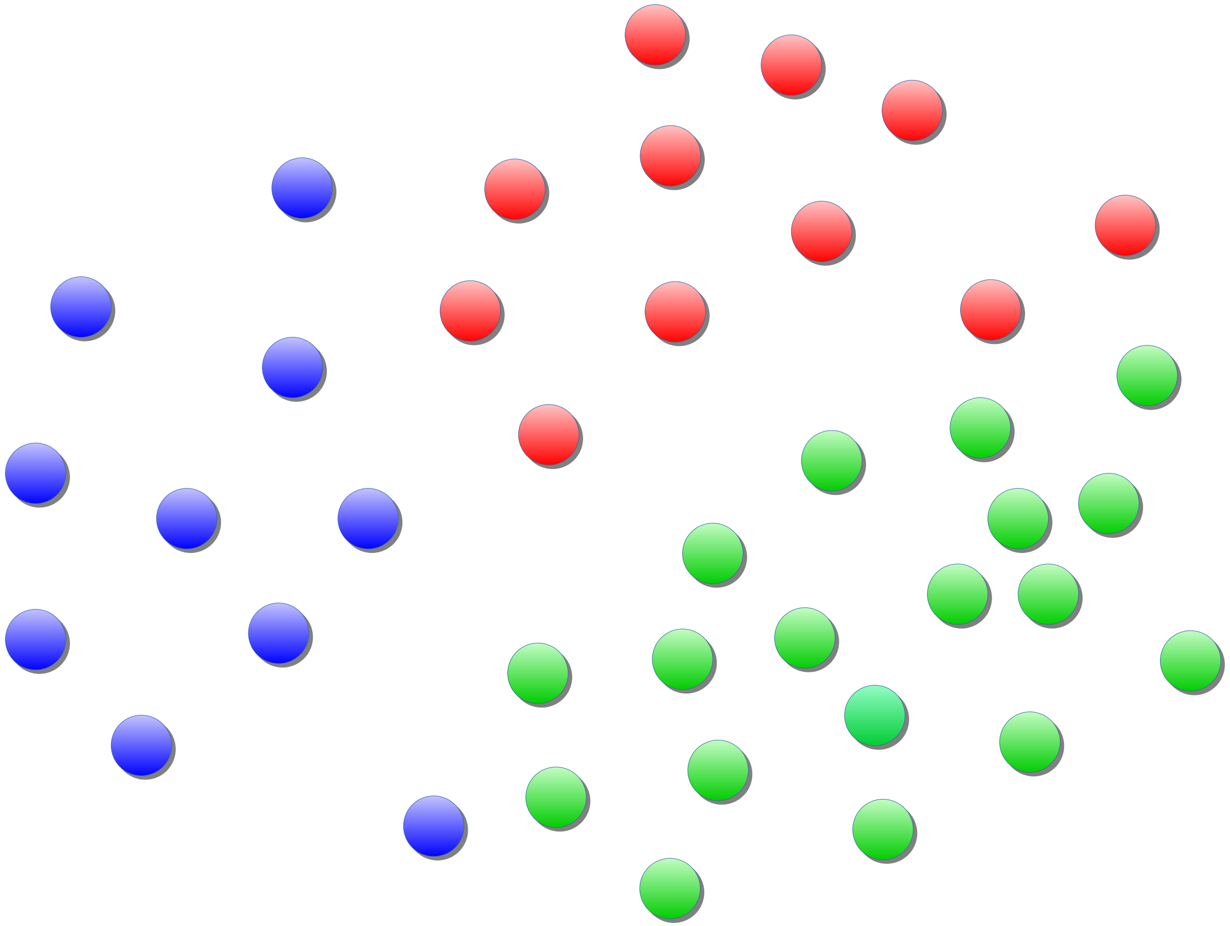
# K-Means (1)



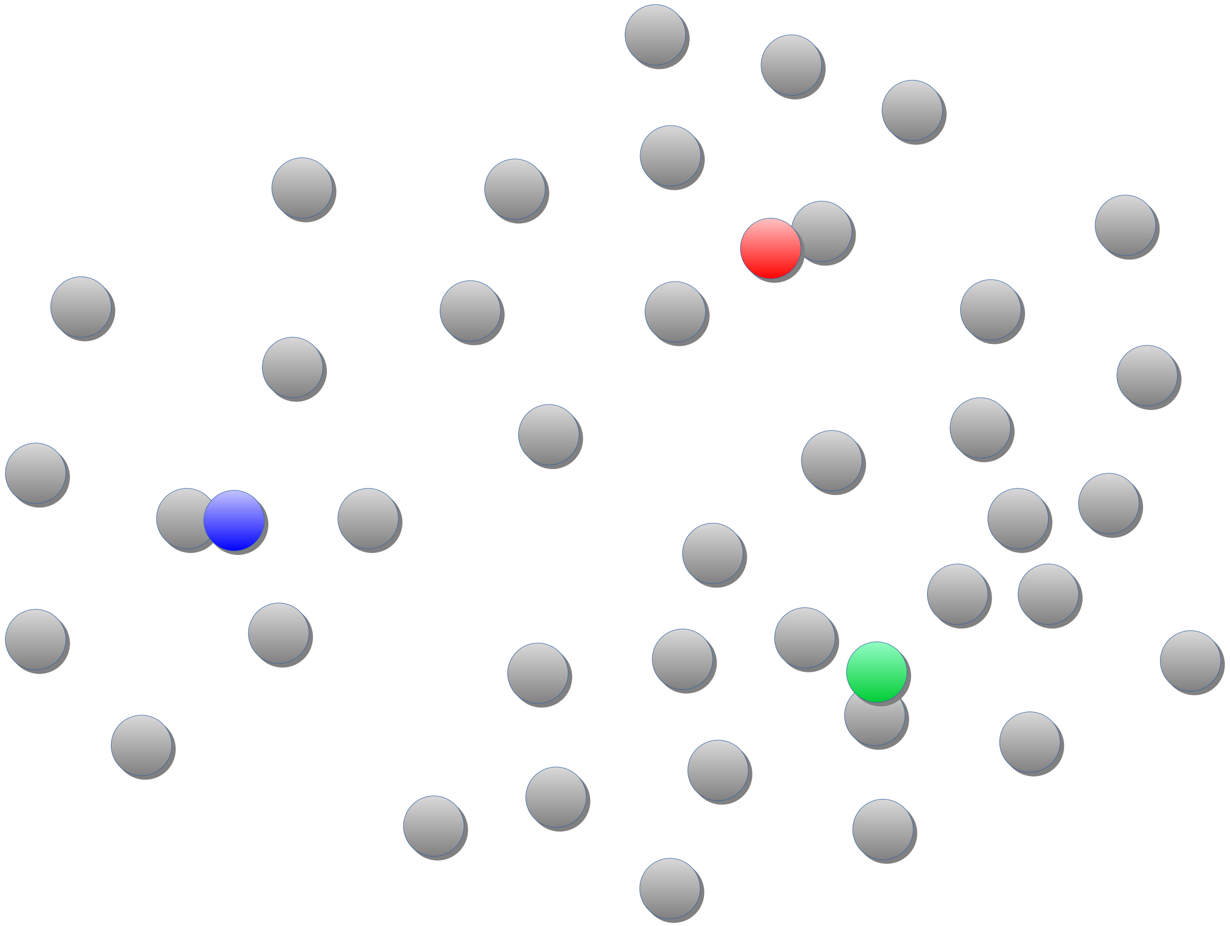
# K-Means (2)



# K-Means (3)



# K-Means (4)



# Pass reward

Imbalance problematic

- Shot within the next ten seconds
  - → extreme imbalance between classes : 10489 vs 194664
- Learned via logistic regression

# The ML element : logistic regression

- Learned from pass examples : x descriptors, **y** success/failure (reward)
  - **Supervised** problem
- Logistic regression :
  - Linear regression $y' = \beta + \beta_1 * x_1 + \beta_2 * x_2 + \dots$
  - The βs are learned
  - Passed through logistic (or sigmoid) function 1/(1+e(-y')) to get well-calibrated results
- *Result between 0 and 1, interpretable as probabilities*
- Assumes linear relationship

# Player assessment

- Individual passes in a play : which player played the one w/highest reward ?
- Passing Plus Minus (PMM) : 1-pass risk if successful, -risk is unsuccessful, normalized per 90 mins
- Difficult pass completion : proportion of passes in 75th percentile completed
- Passes Received Added (PRA) : credit of 1-risk per pass received
- Combine the two as catch-all stat
- Dangerous pass : reward in 75th percentile
  - Again attempted, received
- Evaluated via recourse to « known » players

# Actions speak louder than goals : Valuing Player Actions in Soccer (SciSports paper)

- Event stream data
- Game states labeled w/chance of scoring/conceding
  - In « near » future
- Performing actions → moving from one game state to the next
- VAEP : change probability to score + -1*change probability to concede
- Two classifiers to predict $\text{prob}_{\text{score}}$, $\text{prob}_{\text{concedes}}$
  - Learned via form of **gradient boosted trees**

# Data for learning

- Label : 1 if scored/conceded within the k next states (k=10 in the paper)
- Features : concatenation of $a_{i-2}$, $a_{i-1}$, $a_i$
  - Type, result, body part
  - Start and end locations, distance/angle to goal, distance covered
  - time elapsed since start of game
  - Distance, elapsed time between consecutive actions
  - Game context : goals scored by attacking/defending team, goal difference

**Data transformation/ augmentation**

# The ML element : decision trees

| Weather | Temperature | Humidity | Windy | Play tennis |
|---|---|---|---|---|
| sunny | hot | high | false | No |
| sunny | hot | high | true | No |
| cloudy | hot | high | false | Yes |
| pluvieux | mild | high | false | Yes |
| rainy | cold | normal | false | Yes |
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**Asks questions, partitions data according to answer**

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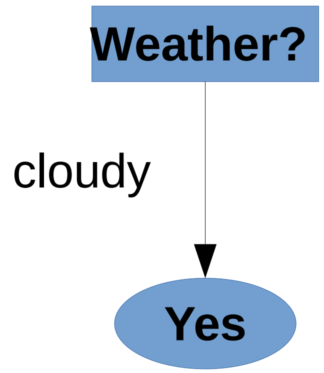

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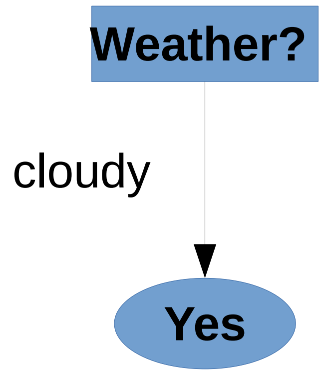

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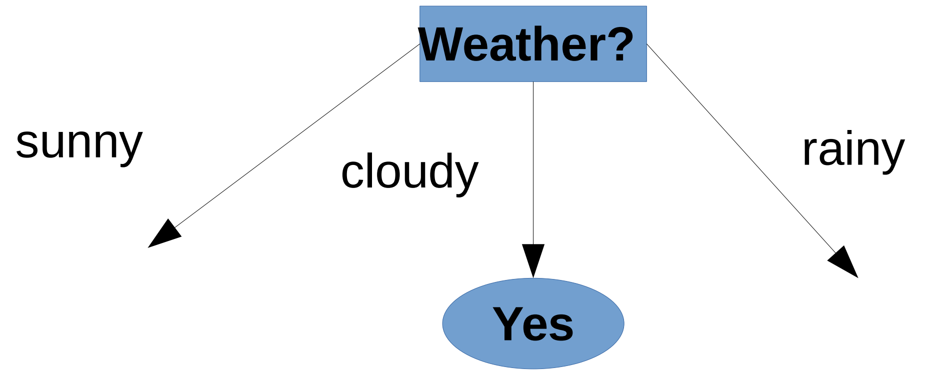

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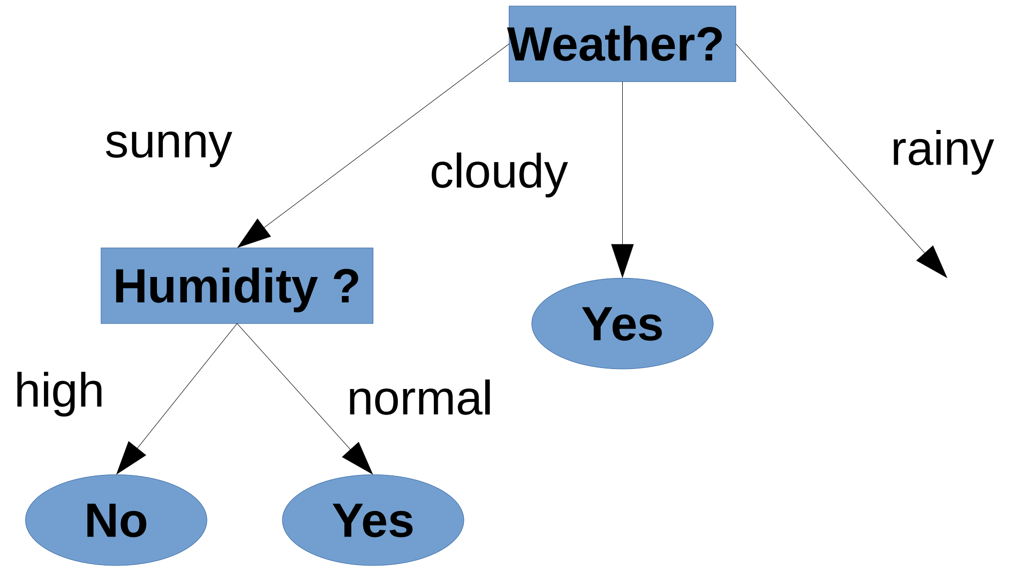

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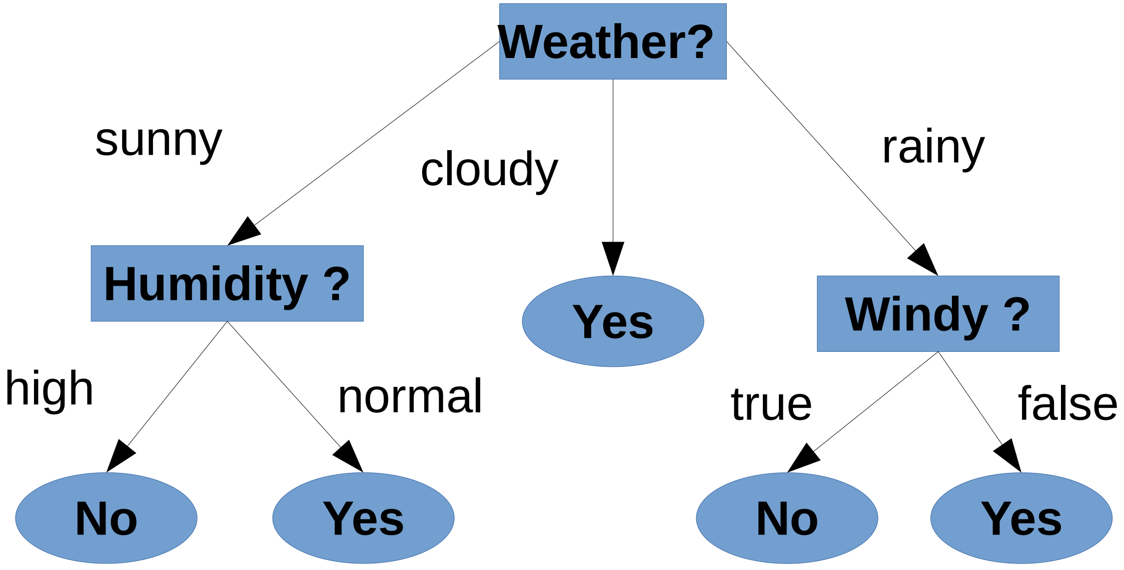

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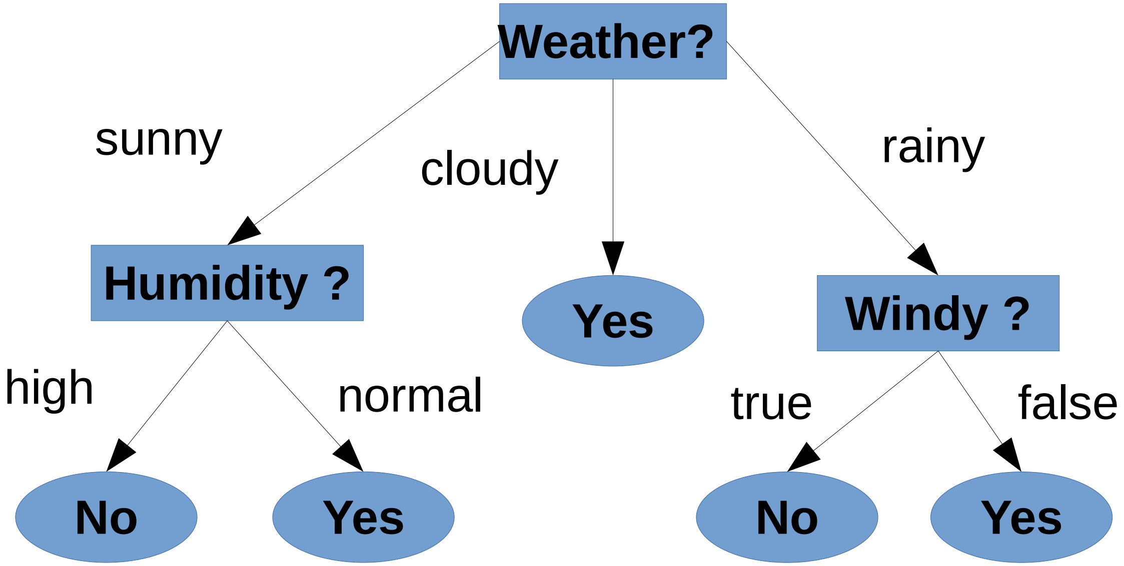



**Tests (questions) learned based on quality function**

# The ML element : boosting

- Learn a succession of classifiers
- Change weight of (label of) mis-classified data points
- Adaboost :
  - Increase weight, instead of 1 mis-classified, have 1.2 mis-classified
- Gradient boost :
  - Cost function with nice derivative
  - Applied to size of error
  - Change label : residual = actual – predicted values
  - Well-classified goes towards 0

# Player rating

- Sum of value of all actions performed by player during time frame, normalized for 90 mins
  - Can be limited to particular action type
- Compared to goals + assists, salaries
- Replacement assessment, Neymar, Cristiano Ronaldo

# Choke or shine (SciSports paper)

Data transformation/ augmentation

- Who performs well (or not) under pressure ?
- Pre-game pressure :
  - Labels : 19 soccer experts rank pairs out of 170 random games (inter-expert agreement 79.79%)
  - Team ambition : **k-means** clustering into 4 groups based on previous result, transfer value of top-20 players, spending on loans, Football manager reputation score
  - Game importance : Elo-based Monte Carlo season simulation, Kendall-Tau correlation between game and season outcome
  - Recent performance : number of points obtained, deviation from expected performance based on Elo
  - Context : location, rivalry (Football manager), attendance, since when coach is there
- Learned used **Gradient Boosted Trees** (**LambdaMART** ) : 73.91 % agreement w/experts

# In-game pressure

- Pressure increases if goal improves chance for favorable outcome, decreases when goal has small influence
- In-game pressure winProb+tieProb **if** team scored in this moment
- Win probability model
  - Future goals based on current state
  - Number of goals scored, goal difference, # yellow/red cards, difference in Elo rating, avg # attacking passed/avg # won duels in previous 10 frames (1 match = 100 frames)
- Learned via **Automatic Differentiation Variational Inference**

# Measuring player performance

- Contribution : improve chance to win ?
  - VAEP
- Quality : were there better options ?
  - Expected contribution over all possible actions – actual contribution
  - Needs probability of success
    - Successful/failed actions, described by locations, body part, locations for previous actions
    - **GBT** as learner
- Execution : how well done ?
  - Actual outcome – predicted probability

# Player assessment

- Pressure levels :
  - High : top-20 %
  - Normal : middle-60 %
  - Low : bottom-20 %
- Contribution rating
  - Avg/90 mins
  - Avg/90 per action type
  - Percentile rank/90
- Decision rating
  - Avg
  - Avg per type
- Execution rating
  - Pct rank per type

# Some results

- Riyad Mahrez better in high-pressure
  - Rachid Ghezzal not a good replacement
- Tom Dwyer commits useless fouls under pressure
- Neymar’s performance declines under pressure
  - Worse decisions

# Deephoops : Evaluating Micro-Actions in Basketball Using Deep Feature Representations of Spatio-Temporal Data

GREYC
Laboratoire de recherche en sciences du numérique

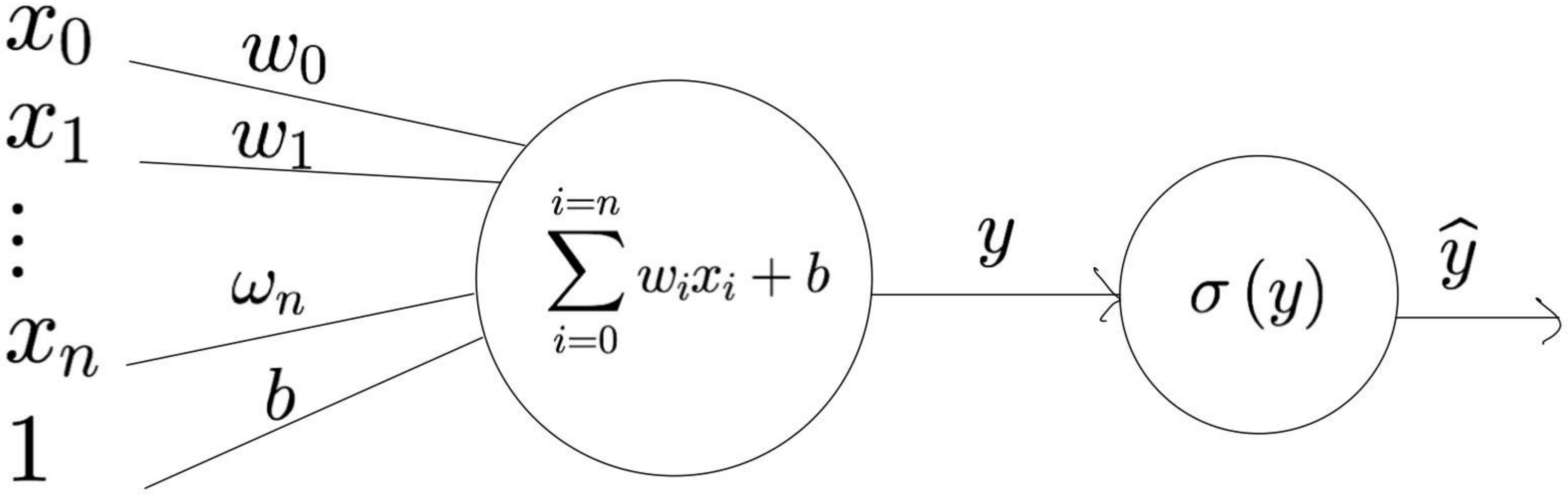
- Micro-actions : screen, pass, backdoor-cut etc
- Player tracking data
  - → moments : vector w/positions of all players, x, y, z of ball, seconds on shot-clock, indicator for the 5 offensive/defensive players, polar coordinates w.r.t. basket of defending team
  - Window of size T=128 (typically several actions during a single possession), annotated with terminal action (field goal attempt, shooting foul, No-shooting foul, turnover, null)
- Distribution of terminal actions learned via **Long Short-Term Memory** neural networks
  - Supervised problem
- Map terminal actions to expected points :
  - Baseline : points/possessions
  - Difference → value of terminal action

**Data transformation**

**32 cells, 3 layers**

**« Null » outweighs rest 600 : 1 → under-sampling**

# The ML element : Neural networks

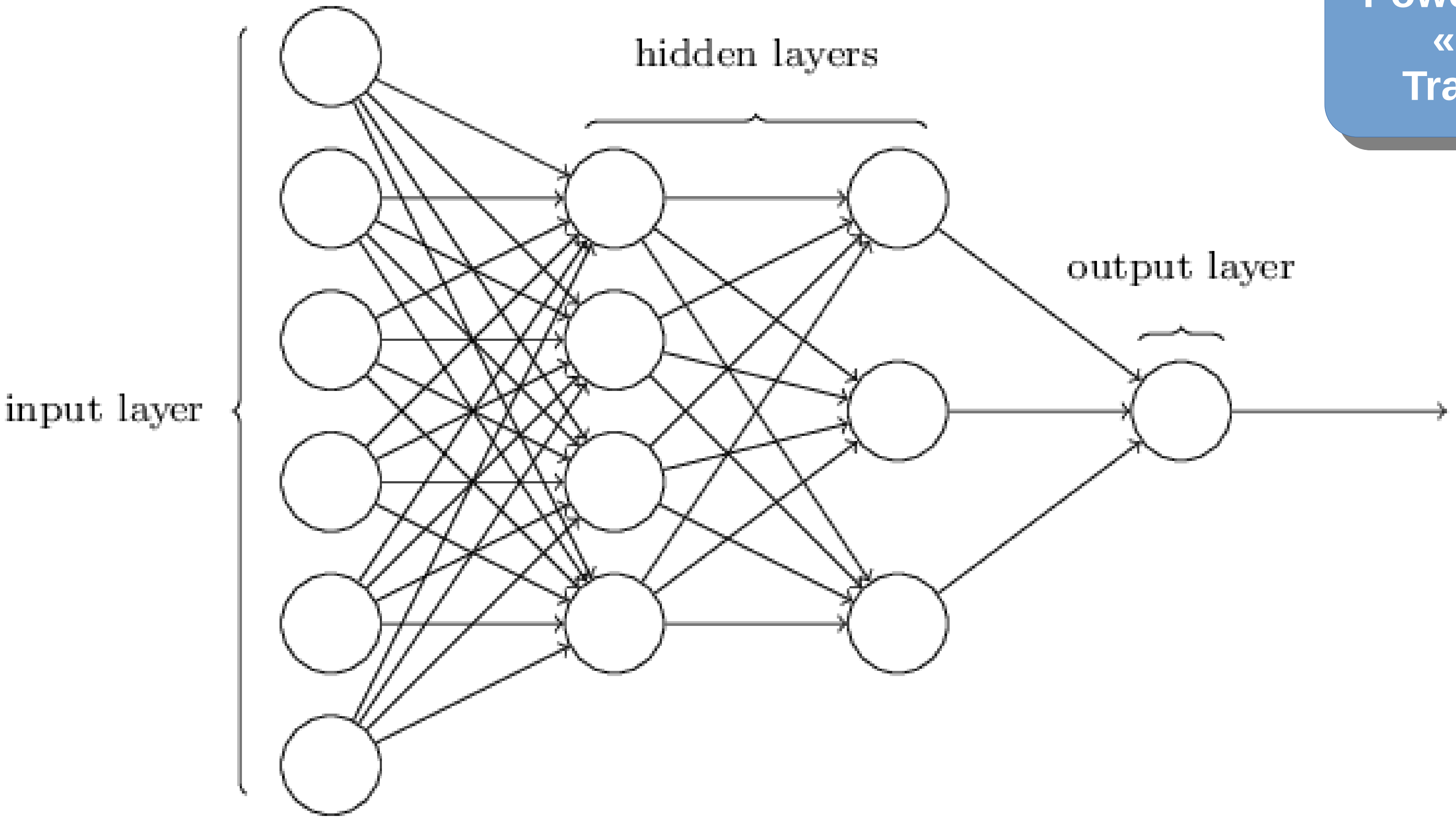



$$y' = \sigma(b + w_0 * x_0 + w_1 * x_1 + \dots w_n * x_n)$$

**Linear regression pass through function ~ logistic regression**

**Rosenblatt '58**

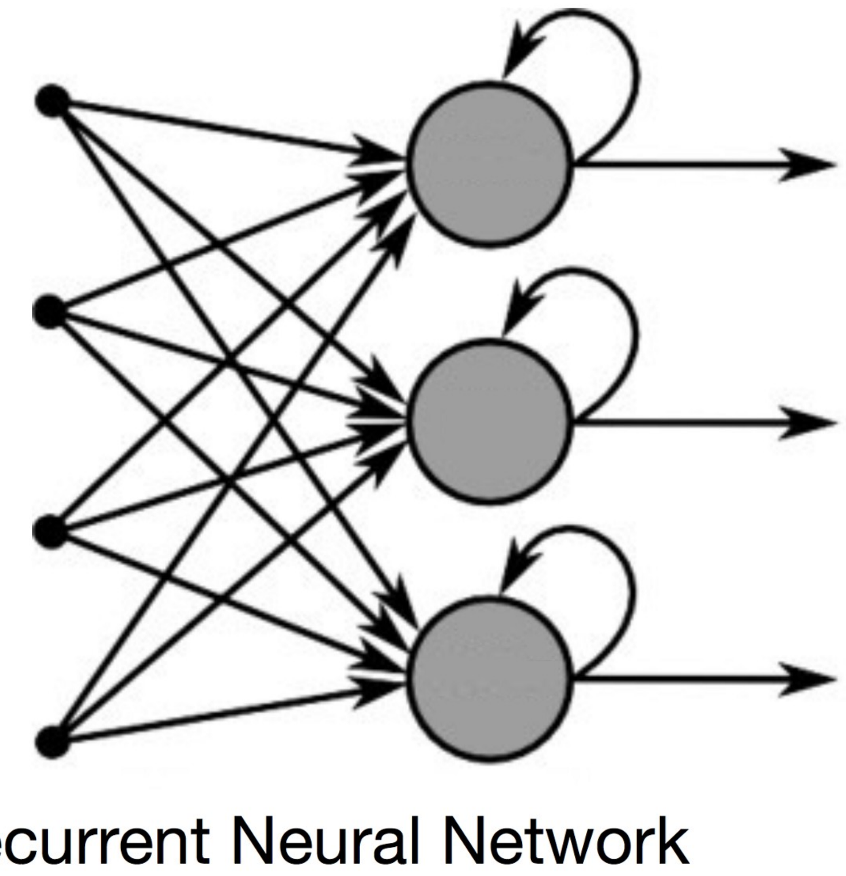
# Neural networks (2)




Power comes from combination
« feed-forward » network
Trained by gradient descent

**Rumelhart, Hinton & Williams '86**

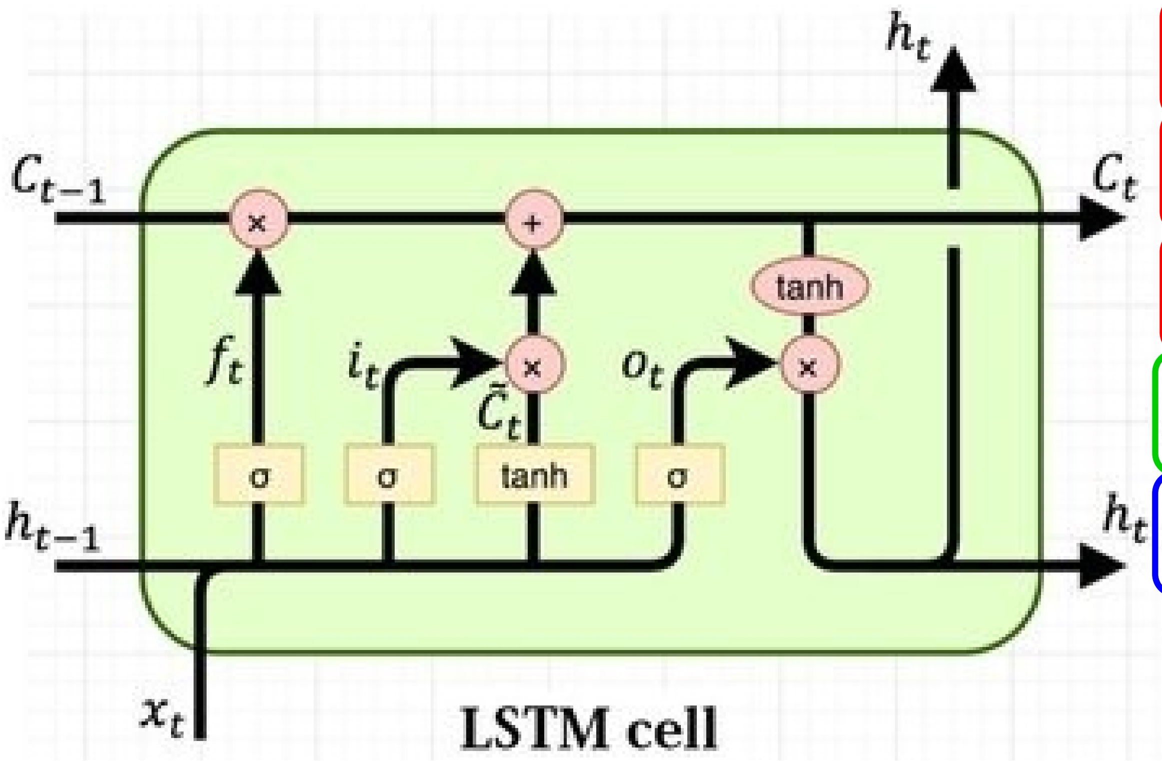
# Dealing w/sequential information : Recurrent neural networks




Problem during learning : error feedback may become overwhelming or disappear for long time lags (>10 steps)

**Older than '89**

# The ML element : LSTM




$$\boxed{i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right)}$$

$$\boxed{f_t = \sigma\left(x_t U^f + h_{t-1} W^f\right)}$$

$$\boxed{o_t = \sigma\left(x_t U^o + h_{t-1} W^o\right)}$$

$$\boxed{\tilde{C}_t = \tanh\left(x_t U^g + h_{t-1} W^g\right)}$$

$$\boxed{C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right)}$$

$$h_t = \tanh(C_t) * o_t$$

**Gated access to cell's « memory » :**
**- input**
**- output**
**- forget**
**originally for whole blocks of cells**

**Hochreiter & Schmidhuber '97**
**Gers et al. '00**

# Player embedding

- Also neural network
- Learned in parallel
- Players w/similar contributions to distribution terminal actions « close » (similar) in learned space
  - Unsupervised problem
- Concatenated w/LSTM output
- Fed into additional dense neural network layer

# Player assessment

- Did player action increase/decrease expected points ?

# Bhostgusters : Realtime Interactive Play Sketching with Synthesized NBA Defenses (Disney research + Stats Inc)

- Where can we expect a defender to be ?
- Player-tracking data
  - Possessions of ten 2D trajectories, one 3D trajectory
  - Game clock, shot clock, player fouls, seconds logged per player
- Modeled by 5 2-layer LSTMs
  - Label to be learned is next position of player
  - Pre-training : predict where player is at next time step, given all other players' positions
  - Individual training : predict positions several steps into future, given all others'
  - Joint training : like invidual but w/predictions of other LSTMs as input

**ANN can have more than one output node...**

# Labels : Expected points to assess actions

- (Potential) shot location
- Ball state
- Distance of two nearest defenders
- Learned via (parsimonious since only few descriptors) regression

# Player assessment

- Was a defending player where he was expected to be ?
- Did a defending player’s positioning best reduce EPM ?
- What offensive actions lead to best EPM ?

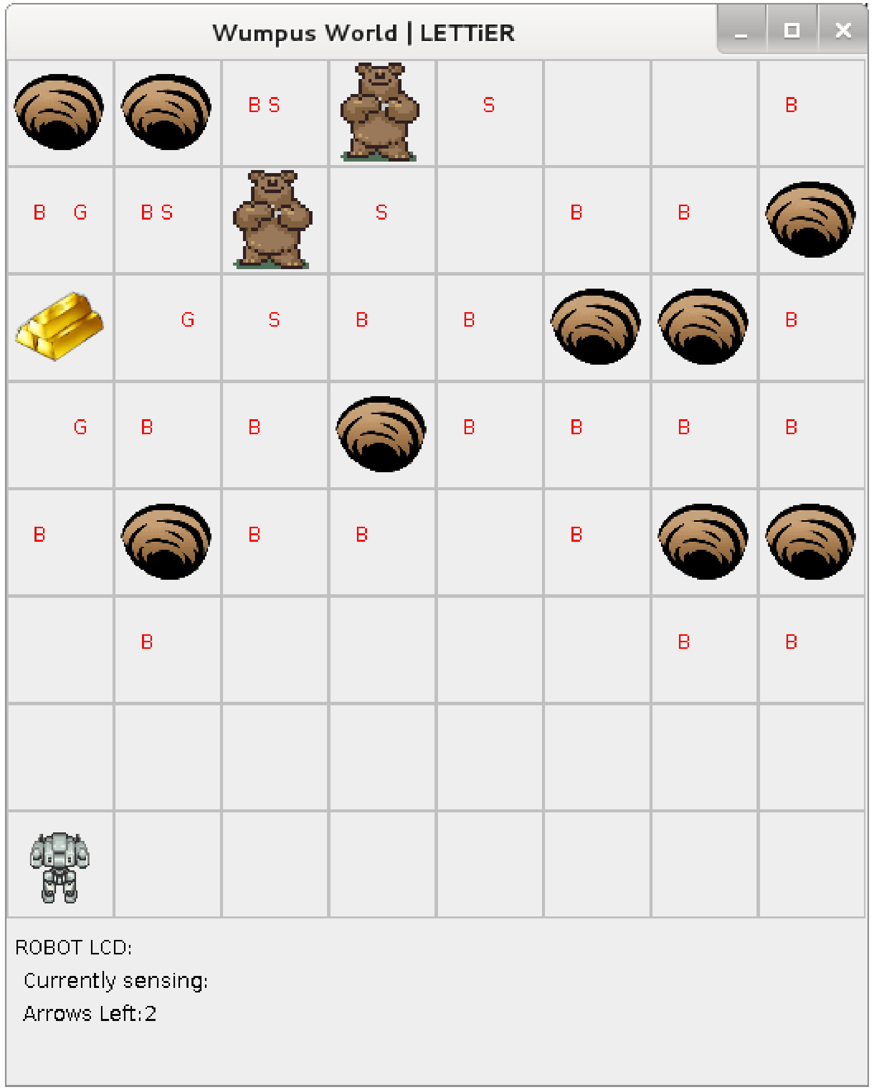
# Deep Reinforcement Learning in Ice Hockey for Context-Aware Player Evaluation

- Event data
- Reinforcement learning
  - 3-dim reward vector : goal scored by home/away/neither
  - 13 possible actions
- Goal-scoring episodes
  - From beginning of game/after goal has been scored
  - To goal scored/end of game

- Learned by DNN
  - Three output nodes
  - 3 hidden layers, 1 LSTM, 2 fully connected
- Temporal difference learning

# The ML element : reinforcement learning

- Neither supervised nor unsupervised
  - Label « changes » with distance from goal
- States of the world
  - Actions → state transitions
  - Action-value function Q(state,action)




**Q-learning : ‘89**

# Player assessment

- Goal Impact Metric (GIM)
  - Change in goal scoring probability of players' team from $s_{t-1}$ to $s_t$
  - Summed over match or season, normalized
- Evaluated via
  - Comparison to NHL stars
  - Salaries
  - Currently used statistics (correlation)

# Takeaway message

- Getting the right data is important
  - And hard/time-consuming/expensive
- Preparing the data might be even more so
  - Requires understanding of the domain
- Deep learning offers powerful methods
  - But it’s not only set of tools
- Evaluation methods are purely academical so far

# Machine Learning and Data Mining for Sports Analytics

- Workshop @ ECML/PKDD
- 8th edition, 13/09/2021
- 17 papers
- https://dtai.cs.kuleuven.be/events/MLSA21/