Erasmus
School of
Economics

Sports Economics: Sports Analytics

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Today

Learning objectives:

1. **Develop and tune a data-driven model to predict match outcomes, evaluate its performance using out-of-sample metrics (e.g., Brier score, accuracy), and compare it against relevant benchmarks.**
2. **Translate model predictions into a transparent betting strategy and assess its profitability and Sharpe ratio using out-of-sample testing.**
3. Create and share a clean replication package (code + data + README) enabling third-party replication.

Today (and previous lecture)

Questions:

1. What forms of Sport Economics and Analytics are there? *(course overview)*
2. **What methods can be used to predict match outcomes?**
3. **How can we tune (hyper) parameters of our model?**
4. **How do we test the performance of our model?**

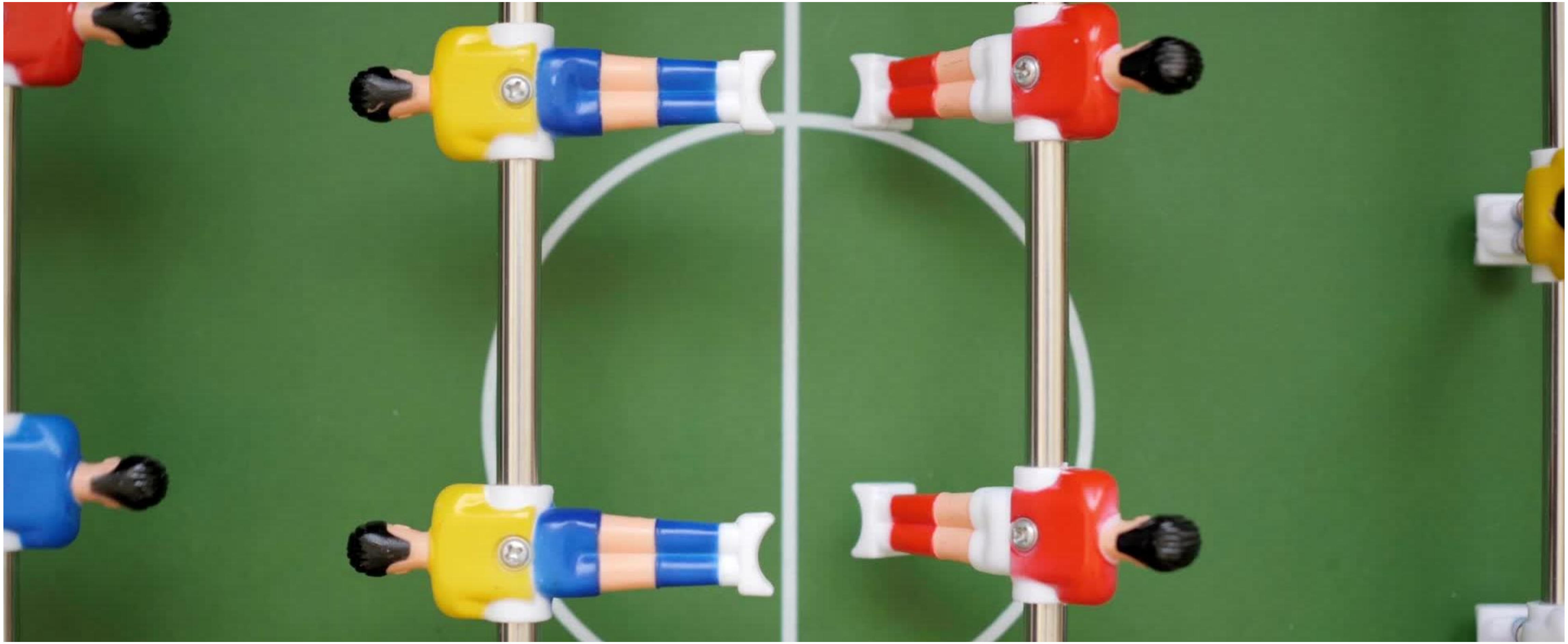
→ I will use some mentimeter quizzes throughout the lecture(s).

Readings

- Academic papers
  - Holmes, B., & McHale, I. G. (2024). Forecasting football match results using a player rating based model. *International Journal of Forecasting, 40(1),* 302-312.
  - Peeters, T. (2018). Testing the Wisdom of Crowds in the field: Transfermarkt valuations and international soccer results. *International Journal of Forecasting, 34(1),* 17-29.
  - Hvattum, L. M., & Arntzen, H. (2010). Using ELO ratings for match result prediction in association football. *International Journal of forecasting*, *26*(3), 460-470.
  - Dixon, M. J., & Coles, S. G. (1997). Modelling association football scores and inefficiencies in the football betting market. *Journal of the Royal Statistical Society: Series C (Applied Statistics), 46(2),* 265-280.

Find them in the literature section in canvas!

Sports Analytics – Match Prediction

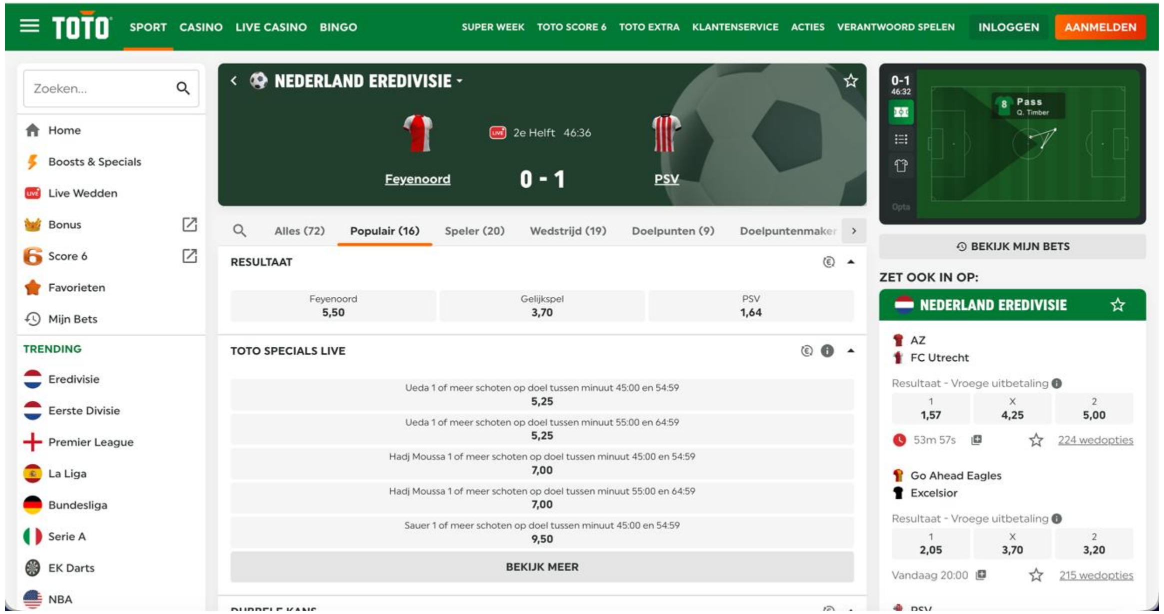


What is there to predict?

Bookmakers generally provide odds for:

Match Outcome (1X2 Market)

- **1:** Home Win
- **X:** Draw
- **2:** Away Win



Proposition bets:

- Goals scored by each team
- Total goals (Over/Under)
- First goal scorer
- Correct score
- Half-time/full-time results
- Shots, corners, penalties, or player-specific events

These markets reflect expectations about team strength and can serve as a useful benchmark for model evaluation.

Match prediction methods

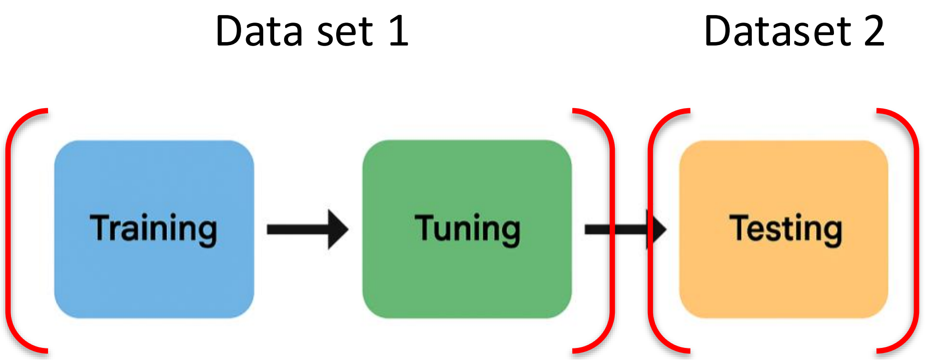
Generally, we use econometric/statistical methods to predict match outcomes

Three Key Stages of Match Prediction Modelling:

1. **Training Stage**
   Choose model and estimate model parameters using historical data.

2. **Tuning Stage**
   Adjust **hyperparameters** (e.g., window size, time decay rate, other features) to optimize predictive performance.

3. **Testing Stage (next lecture)**
   Evaluate model performance on unseen data (test sample) to ensure robustness and avoid overfitting.



→ **Generally**, data is split into a training & tuning subset and a testing subset. **Often,** training and tuning is also split for model tuning.

Training Stage

Goal:

Build the *initial* model by estimating its parameters using **historical data**.

1. **Prepare data**
   - Clean and structure match data (remove errors, ensure time order).
   - Compute relevant features (e.g., team strength, form, ELO ratings)
2. **Estimate model parameters**
   - Fit the chosen econometric/statistical model (e.g., OLS, ordered probit, logistic, Poisson).
   - Learn relationships between covariates and match outcomes.
3. **Assess in-sample fit**
   - Evaluate model fit (BIC, AIC, likelihood, pseudo-R^2, residuals).
   - Identify over-fitting patterns.
4. **Save model outputs**
   - Store estimated parameters, fitted values, and diagnostics.
   - Use these as inputs for tuning and validation.

Leakage: what NOT to do

- Use **end-of-season** stats to predict mid-season games.
- Build features with **future matches** (e.g., last-5 form that includes the target game).

Summary of papers - Training

Core pipeline (all four papers):

- Build a **team strength rating** (goals model / ELO / crowd market values / player-based).
- Form match features (e.g., **rating gap** = Home − Away, plus **home** dummy).
- Convert features → **P(Home, Draw, Away)** with a **multinomial model** such as **ordered probit/logit**.

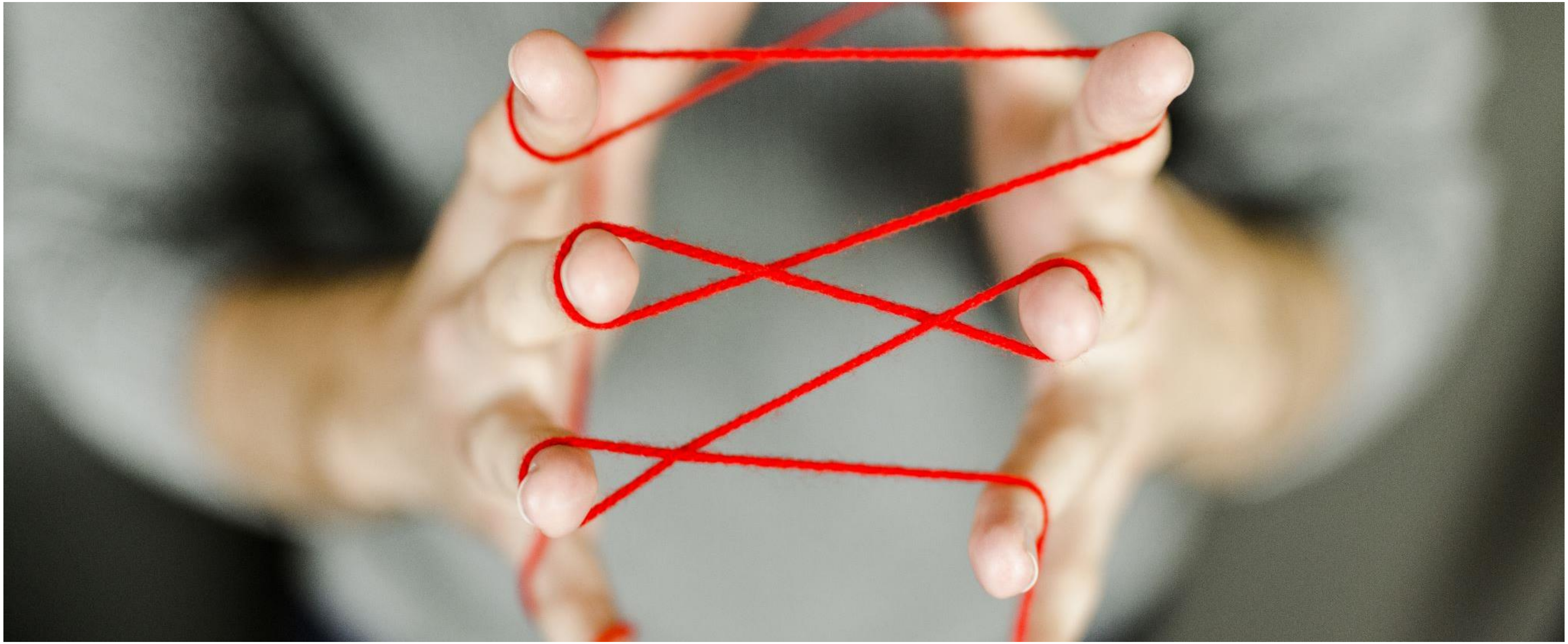
Methods used for building team strength variable:

- Dixon and Coles (1997): home and away strength based on goals scored and conceded
- Artnzen & Hvattum (2010): rolling ELO ratings
- Peeters (2018): wisdom of the crowds measured by TM market values of players
- Holmes and McHale (2024): player-based model with fielded team taken as given.

Methods for within sample goodness-of-fit (Peeters, 2018):

- Psuedo R-squared
- AIC and BIC
- Log-likelihood

Tuning your model



Tuning and Training

Parameters vs. hyper parameters vs. features.

- Parameters are estimated during training or **learned from data**.
  - *Dixon–Coles (1997):* team **attack**, **defence and home advantage,**.
  - *Arntzen & Hvattum (2010):* **ordered-logit** β, relating elo difference to outcomes, and **cutpoints** $\boldsymbol{\tau_1}$ ***and*** $\boldsymbol{\tau_2}$.
  - Can be updated in test data set using **fixed update rule (we do not do this in assignment).**

- Hyper parameters are **chosen** by the researcher
  - **Window length:** how many past matches enter estimation.
  - **Number of seasons included for player ratings** (Holmes & McHale, 2024).
  - **Recency/decay:** weight on past games (Dixon & Coles, 1997; Holmes & McHale, 2024).
  - **ELO update size:** learning rate k → how much ratings move after each game (Arntzen & Hvattum , 2010).
  - Not updated in test data set generally.

- Features/variables are variables that feed into models
  - **Examples:** ELO score, player ratings, Transfermarkt values
  - Can be updated in the test data set using **fixed update rule**

→ We *estimate* parameters and *tune* hyperparameters

→ To tune hyper parameters, we use *benchmarks*.

Benchmarks (needed for tuning)

Accuracy or Success ratio *(higher is better)*

- Evaluates how often the model predicts the right outcome by looking at highest probability outcome and comparing to actual outcome.
- Calculated as the percentage of cases that the model predicts right.
- **Pros:** Simple, intuitive headline metric.
- **Cons:** Ignores probability quality (51% = 99%); sensitive to outcome (im)balance.

Brier score (Quadratic Loss, MSE, or Square of RMSE**,** *lower is better*)

- Evaluates Quality of **probability forecasts** — penalizes being over/under-confident relative to what actually happened.
- **How it's computed (multi-class 1X2):**

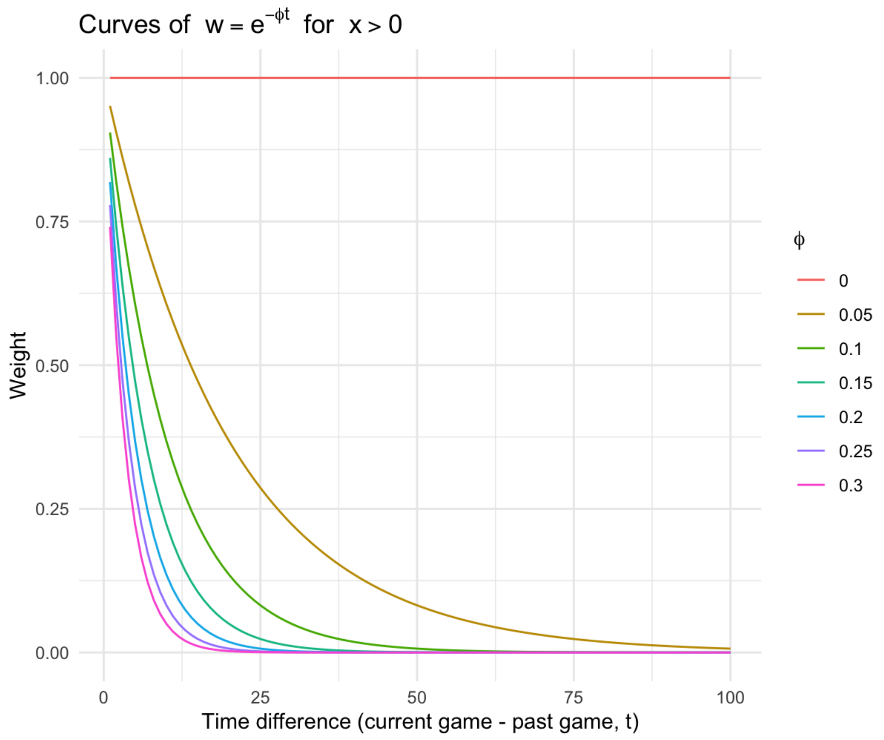
$$Brier = \frac{1}{N}\sum^{N}\sum_{k\in\{H,D,A\}}(p_{ik} - o_{ik})^2$$

  Where p_{ik} = predicted prob for outcome *k (home, draw, away),* $o_{ik} = 1$ if k occurred, else 0.
- Some papers divide by K = 3. **Do not do this in report (we want results to be comparable)**
- **Interpretation:** 0.67 → model as good as random guess, 0 → model predicts perfectly, good score is context dependent
- **Why use it?**
  - Uses full probability distribution (not just top pick)
  - Rewards good well-tuned models

Examples – Tuning decay Parameter

Dixon and Coles (1997) and Holmes and McHale (2024) **tune their time decay parameter**.

- **Dixon and Coles (1997)** less weight on observations further in the past in likelihood function
- **Holmes and McHale (2024)** less weight on player ratings/games (AWS) further in past when calculating player ratings
- Formula: $w_{it} = \exp(-\phi t)$, where t is number of days prior to calculation day.



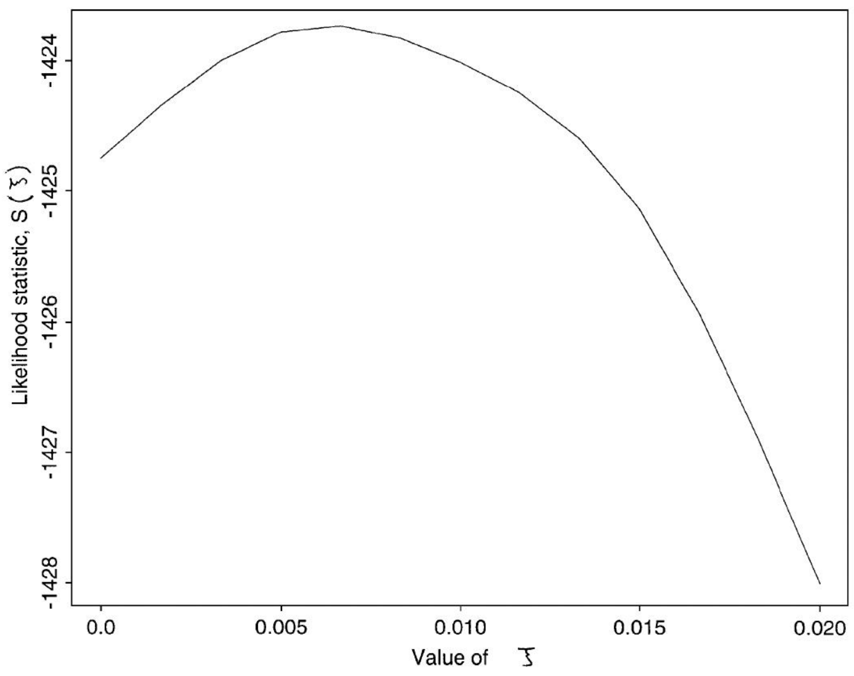


Fig. 1. $S(\xi)$ *versus* ξ: the maximum occurs at $\xi = 0.0065$

Dixon and Coles (1997)

Examples – Tuning updating Parameters

Arntzen and Hvattum (2010) tune two parameters at once

Elo formula:

$$\ell_1^H = \ell_0^H + k(\alpha^H - \gamma^H).$$

k governs the amount of updating;
high k = a lot of weight on most recent game;
low k = less weight on most recent game

Goal adjusted k-factor:

$$k = k_0(1+\delta)^\lambda,$$

k_0 and λ govern updating taking into account goal difference δ

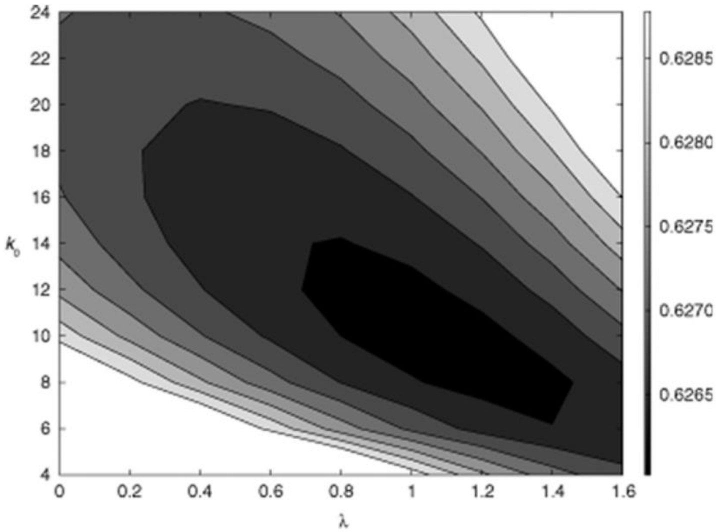
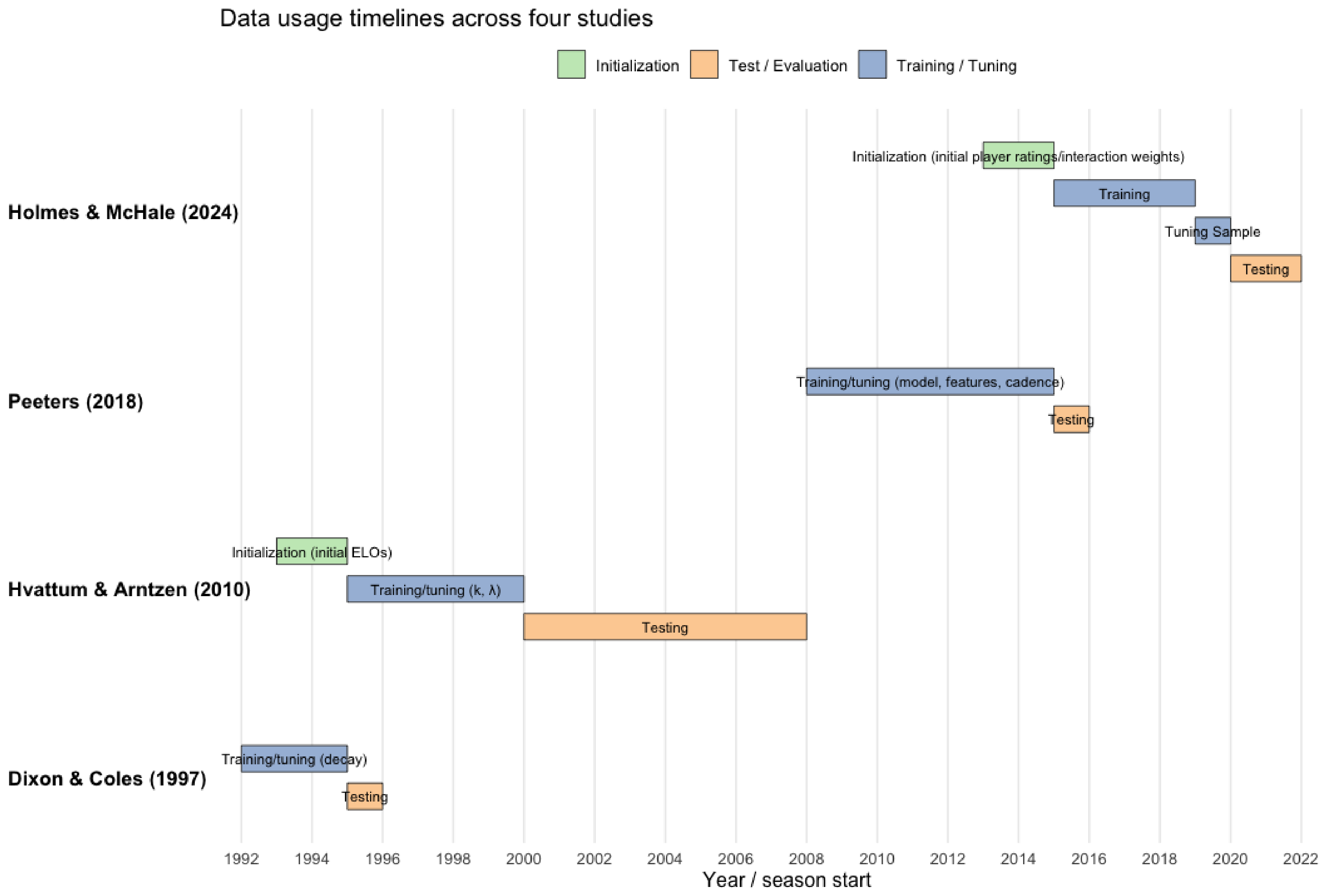


Fig. 1. Observed average quadratic loss when calibrating the two free parameters of the **ELO$_g$** method, k_0 and λ.

They end up using:
k_0 = 10
λ = 1

Model Testing

Training and Tuning Stage Summary



Model Testing

- **What testing is:**
  Check how well your frozen model (parameters + hyperparameters) predicts unseen games → no refitting, no retuning.

- **What overfitting is:**
  When a model learns noise/idiosyncrasies specific too the training data → within sample metrics look great, but out of sample predictions are poor.

- **Why it happens (match prediction):**
  - Too many features based on few observations → noisy parameters
  - Overly aggressive time decay/k (model only considers last few games) .

- **How testing guards against it:**
  A strict chronological test sample (e.g., 2021–2023) reveals whether patterns learned on earlier data (e.g. 2011–2020) actually generalize.

- **Tell-tale signs:**
  Big gap: Train/Validation ≫ Test on Brier Score; overconfidence (probabilities too close to 0/1)

- **Good practice to avoid it:**
  - **Train and tune** parameters and hyperparameters on training & tuning block.
  - **Freeze** parameters & hyperparameters before testing.
  - **Keep it simple:** start with few, well-motivated features.

Keeping it simple (also relevant for training)

Don’t: Add a dummy like **“vs_Bayern”** for each opponent.
Do instead: Use a **strength rating** for the opponent (e.g., ELO or rating gap).
Why: Facing a particular opponent is rare → the model memorizes, not learns.

Don’t: Add home season-specific home advantage parameter for each team.
Do instead: Use one overall home-advantage indicator.
Why: Granular season interacted dummies overfit as they are estimated on few games.

Don’t: Indicators for whether player X is injured
Do instead: Team strength ratings based on players in lineup
Why: for some players injuries might be rare → model memorizes what happened in those specific games.

Morale of the story: Prefer pooled/continuous features over rare, specific dummies so the model generalizes and avoids overfitting.

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Mentimeter

Your connection seems to be unstable. Some features may not work as expected.

Which feature is **most likely to cause overfitting** in a match-outcome model?

Opponent rating gap (home – away)	Overall home-advantage indicator	Referee strictness index	ELO with very high k factor
0	0	0	0

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New presentation

What can we use to predict match outcomes?

past results

form

toto

xg

injuries

home advantage

Which feature is **most likely to cause overfitting** in a match-outcome model?

One concept still fuzzy + one you can explain to a friend.

Evaluating & Benchmarking on Test Data

Metrics (same as tuning): report Brier (primary) and Accuracy on the frozen model.

Benchmarks to compare against:

- Uniform random: p(home, draw, away) = (1/3, 1/3, 1/3) → **Brier = 0.667.**
- Bookmakers' implied probabilities (more later).
- Simple baselines: majority class (Accuracy), historical frequencies (home win, draw, away win).

Model A vs B: Paired t-test on Brier

- For each game t, compute a metric for both methods (e.g., Brier): $b_t^A \; vs \; b_t^B$.
- Run a paired t-test on the per game differences to evaluate whether they are statistically different.
- Equivalently: let $d_t = b_t^A - b_t^B$ → test $H_0 = E[d] = 0$

Arntzen & Hvattum (2010) – Testing Sample Metrics

Table 5

Average values (AVG) and standard deviations (STD) for informational (L^1) and quadratic (L^2) loss on 15,181 matches from the English league system, obtained using eight different prediction methods. The p-values from matched pair t-tests are also reported, comparing each method with $\mathbf{ELO_g}$.

	L^1			L^2		
	AVG	STD	p-value	AVG	STD	p-value
UNI	1.5850	0.0000	0.0000	0.6667	0.0000	0.0000
FRQ	1.5443	0.3791	0.0000	0.6469	0.1870	0.0000
$\mathbf{GOD_b}$	1.5135	0.4824	0.0000	0.6321	0.2371	0.0000
$\mathbf{GOD_g}$	1.5129	0.5136	0.0000	0.6315	0.2472	0.0000
$\mathbf{ELO_b}$	1.5018	0.5030	0.0001	0.6266	0.2475	0.0001
$\mathbf{ELO_g}$	1.4995	0.5060	NA	0.6256	0.2489	NA
AVG	1.4917	0.4772	0.0000	0.6219	0.2340	0.0000
MAX	1.4910	0.4955	0.0000	0.6217	0.2415	0.0000

Brier Score comparison against preferred model ELO_g

Model Testing with Betting Odds

Evaluating & Benchmarking on Test Data

What are odds? (decimal format)

- Decimal odds o: your **total return per \$1 staked** if the outcome wins.
  Example: $o = 2.40$ → win returns \$2.40 (profit \$1.40).

Implied probability

- $p_k^{book} = \frac{1}{odds_k}$ for outcome k (home/draw/away)
- For a fair market, $p_h^{book} + p_d^{book} + p_a^{book} = 1$

Bookmaker maring (overround)

- $R = \sum_k p_k^{book} = p_h^{book} + p_d^{book} + p_a^{book}$ (typically R > 1)
- (R – 1) is the margin spread across outcomes (or the vig)

Converting odds (removing margin)

$$p_k^{fair} = \frac{p_k^{book}}{R}$$

Example:

Odds: Home **2.00**, Draw **3.50**, Away **3.70**

Implied probabilities: 0.500 (home) , 0.286 (draw) , 0.270 (away)

Overround: $R = 0.500 + 0.286 + 0.270 = 1.056$ (≈ **5.6%** margin)

Fair probabilities:

$$p_{home}^{fair} = 0.500/1.056 \approx 0.474$$

$$p_{draw}^{fair} = 0.286/1.056 \approx 0.270$$

$$p_{away}^{fair} = 0.270/1.056 \approx 0.256$$

Expected value (EV) betting

What is EV?

- With decimal odds o and your model probability p:
- $EV = p \cdot o - 1$ is the expected profit per \$1 staked.
  - **EV > 0** ⇒ positive edge (profitable in expectation)
  - **EV = 0** ⇒ break-even
  - **EV < 0** ⇒ negative edge
- Crucial: EV hinges on your *p* being the true probability

Selection rule (typical):

- Bet outcome k only if $EV_k \geq \tau$ (in principle no limits to τ, but typical is from 0% to 5%)
- You can even tune τ in your training/tuning sample to max profits.

Staking (in academic papers)

- Bet **unit stake/flat stake** on most likely outcome when EV threshold is met (default in many papers)
  - Max one bet per match
- Kelly criterion
  - Let $b = o - 1$ (o = bookmaker odds), p = model probability and $q = 1 - p$
  - Kelly fraction: $f^* = \frac{bp-q}{b}$
  - Modified application (Holmes & McHale, 2024): tune EV threshold → if met stake 1 unit x f^* (no bankroll)
  - Can place multiple bets per match.

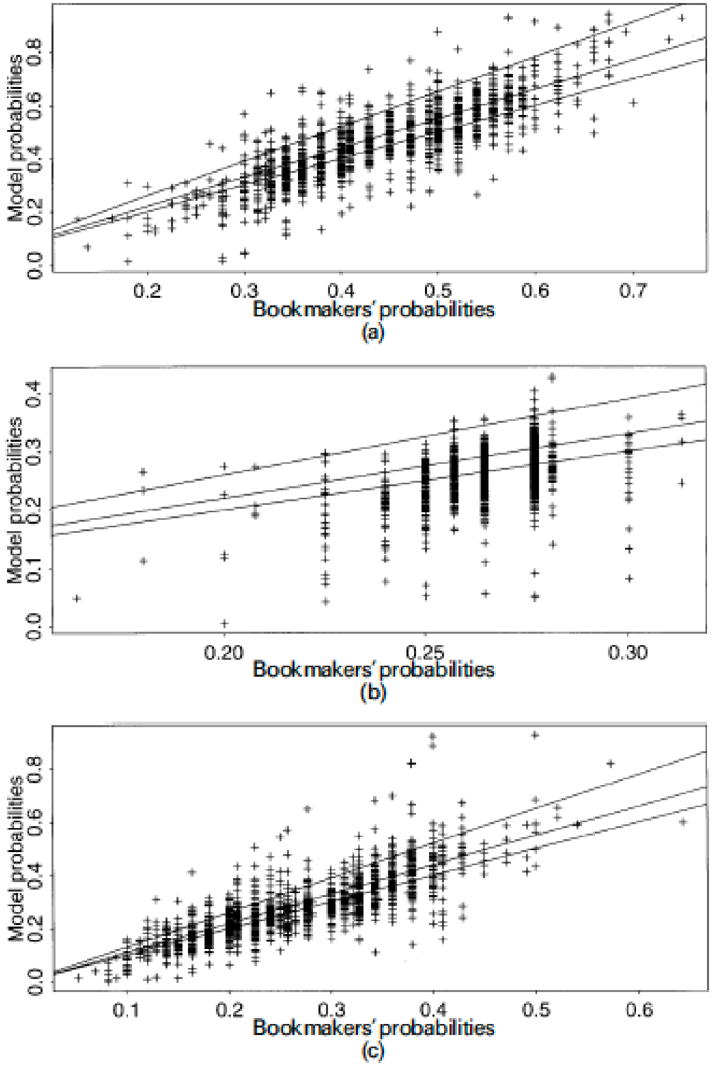
Performance measures

Typical reporting (see Holmes and McHale, 2024):

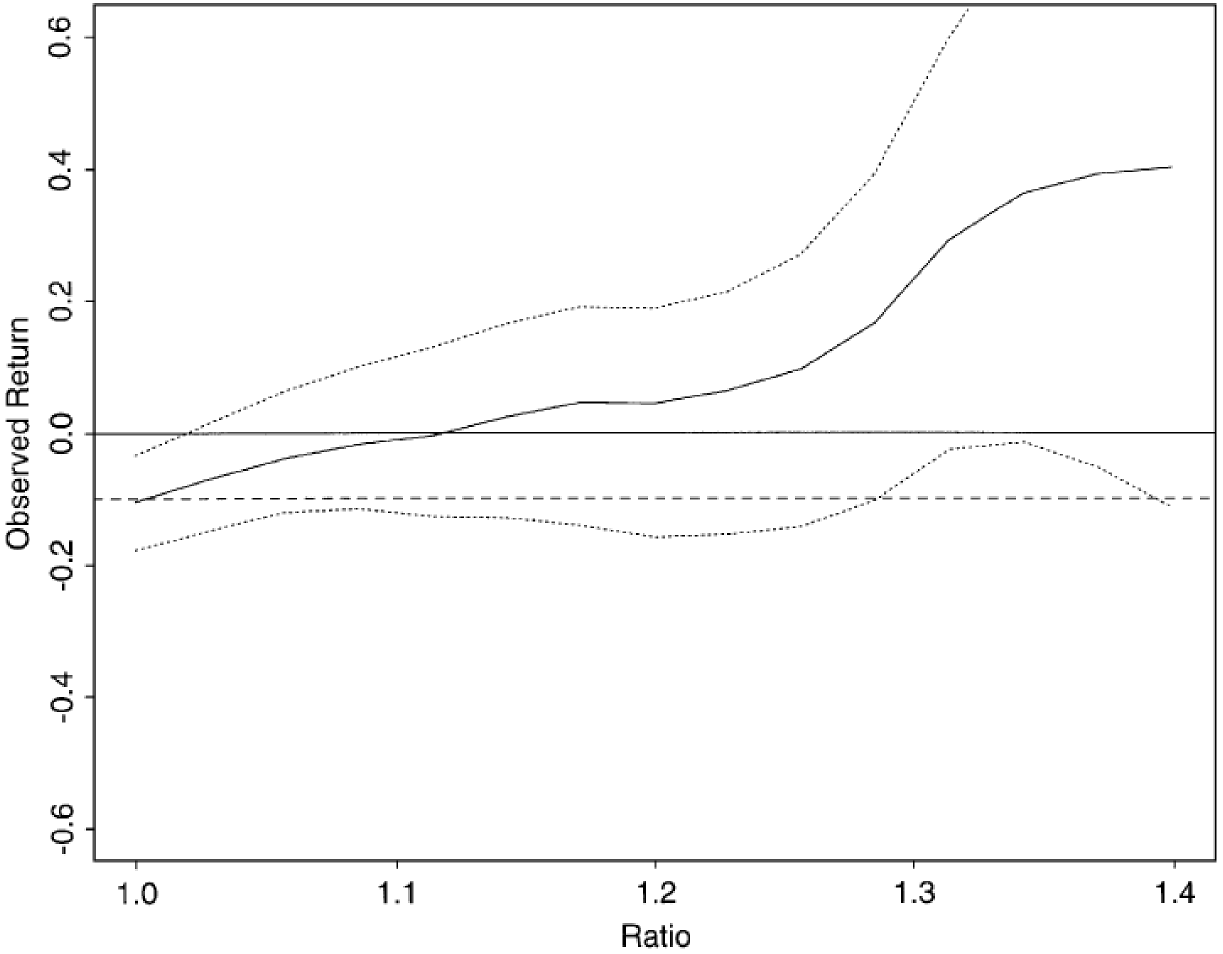
1. Number of bets placed under betting rules (N)
2. EV threshold used
3. Accuracy (hit-rate): how often did bet win (winning bets/N)
4. Profits (returns – stakes)
5. ROI (overall): $return\ on\ investment\ = \frac{profits}{stakes}\ x\ 100\%$
6. Sharpe = $\frac{ROI\ (overall)}{sd(per\ bet\ ROI)} * \sqrt{N}$ (Risk adjusted performance → above 1 is good)

Dixon and Coles (1997)

Model Predictions vs Bookies



Expected RIO for different EV Thresholds, $(1 + \tau)$ here



Why do the confidence bounds expand?

Holmes and McHale (2024)

Table 6
Results for several betting strategies using the skellam$_{full}$ model.

Strategy	t	N	Accuracy (%)	Stakes	Profits	ROI (%)	Sharpe
Kelly	0.1866	556	24.10	65.36	7.81	11.96	1.07
Kelly	0.0000	1457	29.44	105.42	6.03	5.72	1.02
Flat	0.1760	199	37.19	199.00	9.04	4.54	0.45
Flat	0.0000	568	45.25	568.00	16.93	2.98	0.59
Flat		1350	52.00	1350.00	−32.56	−2.41	−0.87

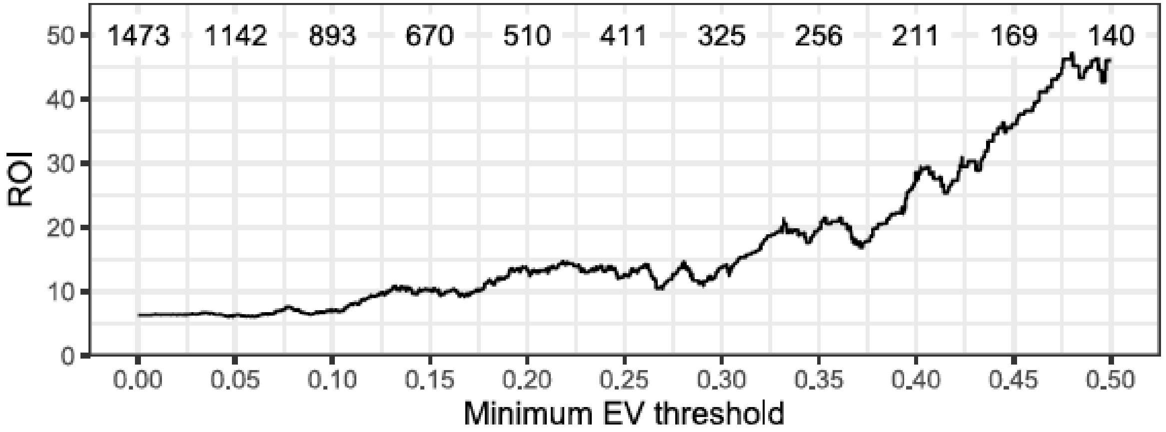


Fig. 5. Plot displaying the ROI that would be achieved using the skellam$_{full}$ model for betting under the modified Kelly strategy for different minimum expected value thresholds.

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Mentimeter

What is true about betting?

0	0	0
Setting a higher EV threshold leads to higher profits.	Higher accuracy (hit-rate) means higher profits.	Sharpe ratio quantifies risk adjusted returns.

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New presentation

What is true about staking?

Which feature is **most likely to cause overfitting** in a match-outcome model?

Training, Tuning and Testing Paper Summary

Study	Model Type	**Training (data & method)**	**Validation (tuning)**	**Test (holdout)**
Dixon & Coles (1997)	Bivariate Poisson for home/away goals	**1992–1995** English league; estimate team **attack/defence** + **home advantage**; exponential time weighting; derive 1X2 from goal model	**Within 1992–1995**: choose **decay parameter** (and low-score tweak) by maximizing predictive score on past matches (time-ordered)	**1995–1996** season; out-of-sample probabilities vs bookmaker odds
Hvattum & Arntzen (2010)	**ELO** ratings + **ordered logit** (rating gap → 1X2)	Initialize ELO on early seasons **1993/94–1994/95**; estimate ordered-logit using ELO on **1995/96–1999/00**	Tune **k_0** (learning rate) and **λ** (margin amplifier) on pre-2000 seasons using **Quadratic Loss (brier)**	**2000/01–2007/08**; evaluate predictive scores and betting simulations
Peeters (2018)	Ordered probit/logit using **Transfermarkt** squad values (crowd signal)	**International matches (UEFA/CONMEBOL) 2008–2014**; predictors: **pre-match** log squad value, home, squad size; rolling estimation	Peeters (2018) does limited tuning: comparing link (probit vs logit), feature sets, and daily vs monthly updating	**Out-of-sample windows** (held-out periods, e.g., later seasons/tournaments); compare to bookmakers, ELO, FIFA
Holmes & McHale (2024)	Multinomial with **player-based** team strength (incl. pair/position effects)	Pre-train positional/interaction models **2013/14–2014/15**; training/tuning window **2015/16–2020/21** using player ratings	**Inside 2015/16–2020/21**: first **80% train**, **last 20% of that block validate**; tune **decay parameter**, shrinkage, interaction set, EV threshold	**2020/21-2021/22**; fixed parameters; report Brier/accuracy and betting vs bookmakers

Assignments

Assessment – Group assignment (40% of final grade)

Report 1 — Match-Outcome Prediction (30% of final grade)

- **Deadline:** Mon 24 Nov, 12:00 (noon)
- **Data: NHL data provided**
- **Tasks:**
  - Build a probability based model to predict NHL match outcomes.
  - Provide model evaluation scores and compare against relevant benchmarks.
  - Provide results for different betting strategies based on probability model.
- **Deliverables:** PDF report, code, log files and dataset.

Report 2 — Peer Evaluation and Verification (10% of final grade)

- **Deadline:** Fri 5 Dec, 12:00 (noon)
- **Data:** After checks I will distribute replication packages from assignment 1
- **Tasks:**
  - **Replicate another group's results** from their code and **verify their benchmarks**.
  - Compare **your model vs other group**; explain similarities/differences.
  - Document any replication issues and propose fixes.
- **Deliverables:** PDF report & replication log.

Hackathon:
In lecture 10 we will compare results across groups and highlight what strategies/prediction models worked best.

Assignment 1 – Overview (See Assignment for more detail)

1. Predict **Home / Tie / Away** for using National Hockey League data provided on canvas.
2. Show your **decision process**: alternatives considered → final choice.
3. Evaluate with **Brier**, **Accuracy** (out-of-sample).
4. Convert predictions into a **transparent betting strategy**; report **profitability** & **Sharpe**.
5. **Groups:** 4–5 students · **Limit:** 11 pages (1.5 spacing, font 11) · **Deadline: Mon 24 Nov, 12:00**.
6. Include a short **AI reflection** (how you used ChatGPT, what you accepted/rejected).

Assignment 1 - Data Split & Workflow (See Assignment for More detail)

1. **Train + Validate: 2011–2020**
   - Try models; **tune**: window length, **decay**, feature set/variables, thresholds.
2. **Test (strict holdout): 2021–2023**
   - **No** tuning/refitting after freeze → parameters and hyperparameters fixed.
3. **Betting simulations: only** on 2021–2023 **after** tuning is frozen.
4. **Report:** training & tuning (for model and hyperparameter choices) and **final test** results (for performance).

Assignment 1 – Structure (see assignment for more detail)

Introduction

- Problem & contribution; modeling options considered (3+ papers cited)
- Final model preview & why (brief)

Data

- Sample: NHL games, **Train/Validate 2011–2020**, **Test 2021–2023**
- Sources, data cleaning, key variables, summary tables/figures

Methodology

- Model(s) and features, **tuning** (e.g. window width, decay)
- Odds → rescale probabilities for bookmaker benchmark
- Anti-leakage design; reproducibility choices

Model Performance (Test: 2021–2023)

- **Brier & Accuracy** vs. benchmarks (incl. bookmakers)
- Betting simulation: rules (EV threshold, staking), **ROI/Sharpe**

Conclusion

- Main findings; limitations

AI Reflection (last page)

- How AI helped; accepted vs. rejected suggestions; verification steps

Assignment 1 – Rules of the Game (see assignment for more detail)

1. **Fixed split** into training & tuning data and test data (2021 season onwards)
2. **Freeze** all parameters & hyperparameters **before** touching the test set.
3. **Only pre-game info** at prediction time (no end-of-season stats for earlier games).
4. **Time-updating features/variables allowed** in test data (e.g., rolling form/ratings) **if** updates follow the **pre-specified rule**.
5. **Player-based models:** you may treat the **listed lineup** as known pre-puck drop.
6. Keep full **reproducibility**: fixed seeds if needed , well documented, one-click run after Working Directory change.
7. AI is allowed (and encouraged), but use of it must be documented.

Assignment 1 – Deliverables (see assignment for more detail)

Report (PDF): se_assignment1_<group_number>_report.pdf

Code:

- **R:** se_assignment1_<group_number>_code.R
- **Stata:** se_assignment1_<group_number>_code.do

README (PDF): se_assignment1_<group_number>_README.pdf (how to run, software, seeds)

Data (CSV): se_assignment1_<group_number>_data.csv

- Make it **end-to-end runnable** without manual steps; document everything clearly.

Assignment 1 – Evaluation Criteria (see assignment for more detail)

1. **Model choice process:** alternatives tested, **tuning strategy**, clear reasoning.
2. **Benchmarking & metrics: Briers**, **Accuracy**; compare to **relevant benchmarks**.
3. **Betting strategy:** correct implementation; transparent rules (**EV threshold**, staking, cap); report **ROI & Sharpe** (test set only).
4. **Clarity & documentation:** well-written, cited relevant papers; neat layout.
5. **Reproducibility:** code/data/README produce identical results.

Assignment 2 – Overview (see assignment for more detail)

Role: Independent verifier of another group's model and replication package.

Verification (2021–2023 test only):

- Run their code **as provided** (no edits/tuning).
- Reproduce **Brier** and **Accuracy**; record exact values.
- If non-replicable, **document discrepancies** (seeds, versions, missing files, paths).

Evaluation (method & practice):

- Is the **README** clear? Does code run **end-to-end**?
- Does the design follow good practice (**chronological split**, **freeze before test**, **no leakage**, sensible **window/decay**, odds handling)?
- Are results **robust** and **interpretable**? Any red flags?

Reflection:

- What would you **adopt** or **change** in your own workflow? Why?

Deliverables (3 pages max):

- **Report PDF**: verification results, evaluation, reflection.
- **Run log**: proof of execution / where it failed.
- **Practicalities:** same group as A1; 1.5 spacing, font 11; **deadline: Fri Dec 5, 12:00**; include brief **AI reflection if used.**

Note: this report has no influence on Assignment 1 grading.

Assignment 2 – Evaluation Criteria (see assignment for more detail)

1. **Verification of results:**
    - Successfully reproduce out-of-sample Brier & Accuracy on 2021–2023, or give a clear, evidenced account of discrepancies.

2. **Methods & reproducibility:**
    - Evaluation of model design & tuning (leakage control, freeze, window/decay, odds handling).
    - Evaluate reproducibility: README clarity, one-click code run.

3. **Reflection & adaptation:**
    - Concrete, actionable improvements you'll make to your own model/workflow or to theirs.

4. **Clarity & documentation (presentation):**
    - Tight, well-structured ≤3 pages; labeled figures/tables; precise reporting of metrics and any errors/logs.

Musts: do not modify their model and attach a run log.

Data assignment clinics

- Voluntary opportunity to get feedback for your group
  - Private Q&A with 1 teacher
  - Only assignment questions

- Planning:
  - Data clinic 1: Wednesday 12 November (scheduled appointments on Teams/Campus)
    - Proposal deadline: Monday 27 November
  - Data clinic 2: Wednesday 19 November (scheduled appointments on Teams/Campus)
  - **Report 1 deadline: 24 November** 12h00
  - Data clinic 3: Wednesday 3 December (scheduled appointments on Teams/Campus)
  - **Report 2 deadline: 5 December 12h00**

<u>!!!! Send e-mail to sportecon@ese.eur.nl at least 2 days before to set appointment for your group!!!!</u>

Join at menti.com | use code 5605 4055

Mentimeter

One concept still fuzzy + one you can explain to a friend.

All responses to your question will be shown here

Each response can be up to 200 characters long

Turn on voting to let participants vote for their favorites

0 / 31

SH

Menti

New presentation

injuries
home advantage

One concept still fuzzy + one you can explain to a friend.

What do you associate with sports economics and analytics?

betting
data
winning
losing
predictions