# Representation Matters for Mastering Chess: Improved Feature Representation in AlphaZero Outperforms Switching to Transformers

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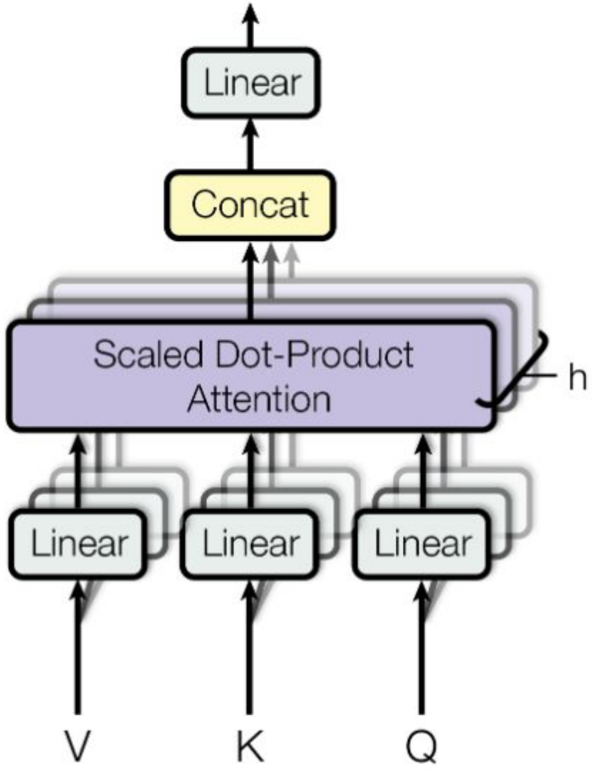
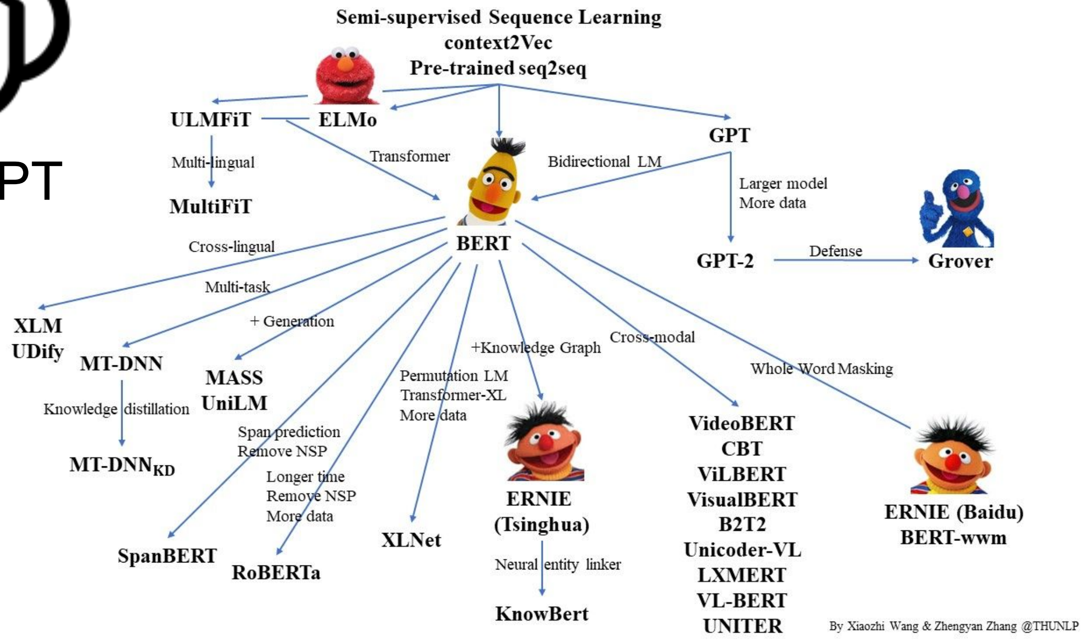
# Success Stories of the Transformer Architecture




Multi-Head Attention Block of the Transformer architecture [VSP+17]

ChatGPT




The transformer architecture is used in many Large Language Models (LLMs)

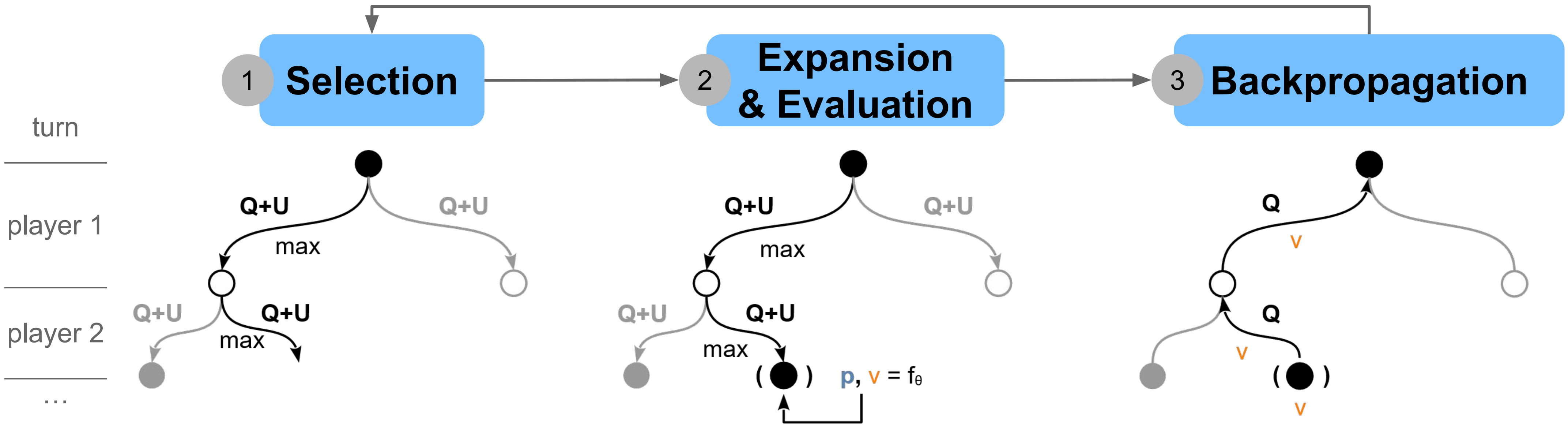
# Success Stories of the Transformer Architecture

- Have transformers become the **“Swiss Army Knife” of AI?**

# Success Stories of AlphaZero

## Remarkable Examples with ≤ 2 Players

- Chess, Shogi, and Go above grandmaster level [SHS+18]
- Mastering Atari with a learned environment model [SAH+20]




MCTS Phases in AlphaZero [SHS+18] based on a design by Deepmind.

# Feature Engineering

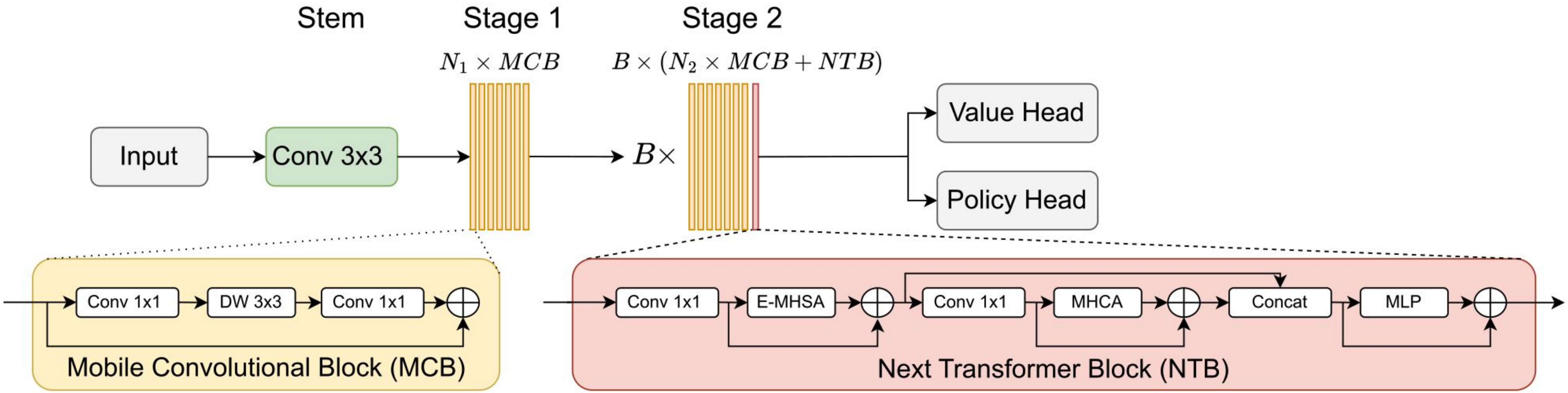
- **“Deep Learning removes the need for feature engineering”** – François Chollet

François Chollet

# Research Questions

- (Q1) Is the combination of AlphaZero with Vision Transformers beneficial in the game of chess?
- (Q2) How important is the input and output representation for AlphaZero?

# AlphaVile Architecture: CNN + ViT




- Hybrid architecture of Mobile Convolutional Block [SHZ+18] and Next Transformer Block [LXL+22]
- Classical AlphaZero network design: shared neural network with two outputs

# Feature Extension: The Importance of Representation

| Feature | Planes | Type | Comment |
|---|---|---|---|
| P1 pieces | 6 | bool | order: {PAWN, KNIGHT, BISHOP, ROOK, QUEEN, KING} |
| P2 pieces | 6 | bool | order: {PAWN, KNIGHT, BISHOP, ROOK, QUEEN, KING} |
| Repetitions* | 2 | bool | how often the board positions has occurred |
| En-passant square | 1 | bool | the square where en-passant capture is possible |
| ~~Color~~* | 1 | bool | all zeros for black and all ones for white |
| ~~Total move count~~* | 1 | int | integer value setting the move count (UCI notation) |
| P1 castling* | 2 | bool | binary plane, order: {KING_SIDE, QUEEN_SIDE} |
| P2 castling* | 2 | bool | binary plane, order: {KING_SIDE, QUEEN_SIDE} |
| No-progress count* | 1 | int | sets the no progress counter (FEN halfmove clock) |
| Last Moves | 16 | bool | origin and target squares of the last eight moves |
| is960* | 1 | bool | if the 960 variant is active |
| P1 pieces | 1 | bool | grouped mask of all P1 pieces |
| P2 pieces | 1 | bool | grouped mask of all P2 pieces |
| Checkerboard | 1 | bool | chess board pattern |
| P1 Material difference* | 5 | int | order: {PAWN, KNIGHT, BISHOP, ROOK, QUEEN} |
| Opposite color bishops* | 1 | bool | if they are only two bishops of opposite color |
| Checkers | 1 | bool | all pieces giving check |
| P1 material count* | 5 | int | order: {PAWN, KNIGHT, BISHOP, ROOK, QUEEN} |
| Total | 39 / 52 | | |

We added several features:

- piece mask for player 1 and 2
- checkerboard pattern
- material difference information
- opposite color bishop information
- checking pieces
- material count for player 1

We removed several features:

- color information
- total move count

# Feature Extension: The Importance of Representation

| Size | $B$ | $N_1$ | $N_2$ | # Blocks | Base Channels |
|---|---|---|---|---|---|
| AlphaVile (tiny) | 1 | 8 | 6 | 15 | 192 |
| AlphaVile (small) | 1 | 11 | 10 | 22 | 192 |
| AlphaVile (normal) | 2 | 10 | 7 | 26 | 224 |
| AlphaVile (large) | 2 | 13 | 11 | 37 | 224 |

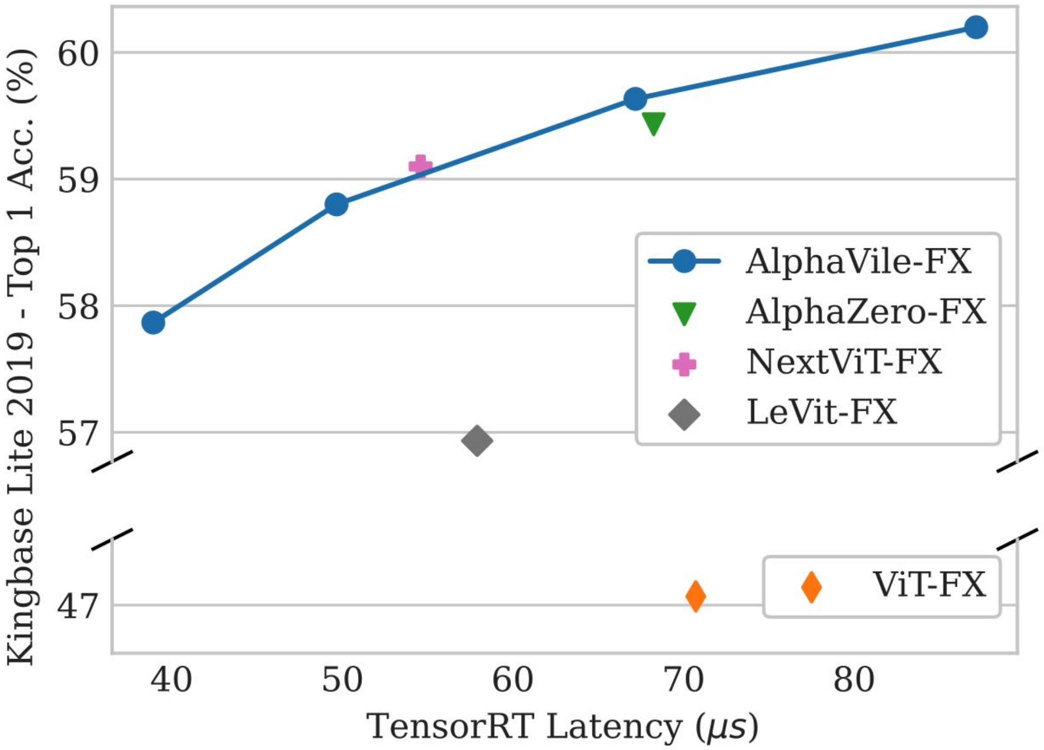
| Input Representation | Combined Loss | Policy Acc. (%) | Value Loss | Latency ($\mu s$) |
|---|---|---|---|---|
| Inputs V.1.0 | $1.1918 \pm 0.0028$ | $58.63 \pm 0.05$ | $0.4448 \pm 0.0007$ | **52.08** |
| Inputs V.2.0 | $\mathbf{1.1901 \pm 0.0049}$ | $\mathbf{58.67 \pm 0.17}$ | $\mathbf{0.4371 \pm 0.0002}$ | 53.54 |

| Value Head Type | Combined Loss | Policy Acc. (%) | Value Loss | Latency ($\mu s$) |
|---|---|---|---|---|
| MSE | $1.1933 \pm 0.0021$ | $58.50 \pm 0.08$ | $0.4406 \pm 0.0002$ | **53.35** |
| WDLP | $\mathbf{1.1901 \pm 0.0051}$ | $\mathbf{58.73 \pm 0.12}$ | $\mathbf{0.4356 \pm 0.0006}$ | 53.38 |

- AlphaVile is available in various sizes
  - tiny
  - small
  - normal
  - large
- Inputs V.2.0 outperform Inputs V.1.0, especially with regards to the value loss
- The Win-Draw-Loss-Plys-to-end (WDLP)[2] value head scores better than the Mean-Squared-Error (MSE) one

2: WDLP head by Henrik Forstén: https://github.com/LeelaChessZero/lc0/pull/635

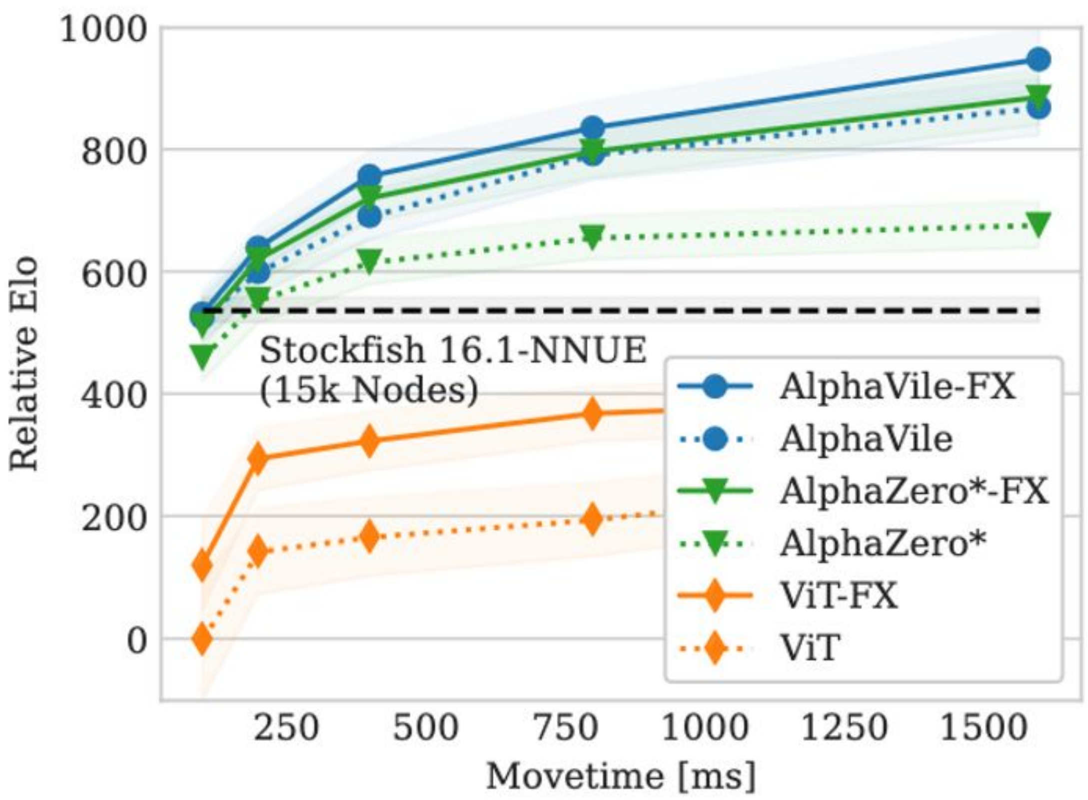
# Results: Validation Move Accuracy




- The standard ViT severely underperforms
- Supervised training on the KingBase 2019 lite dataset[3]
- AlphaVile-normal is slightly better than AlphaZero

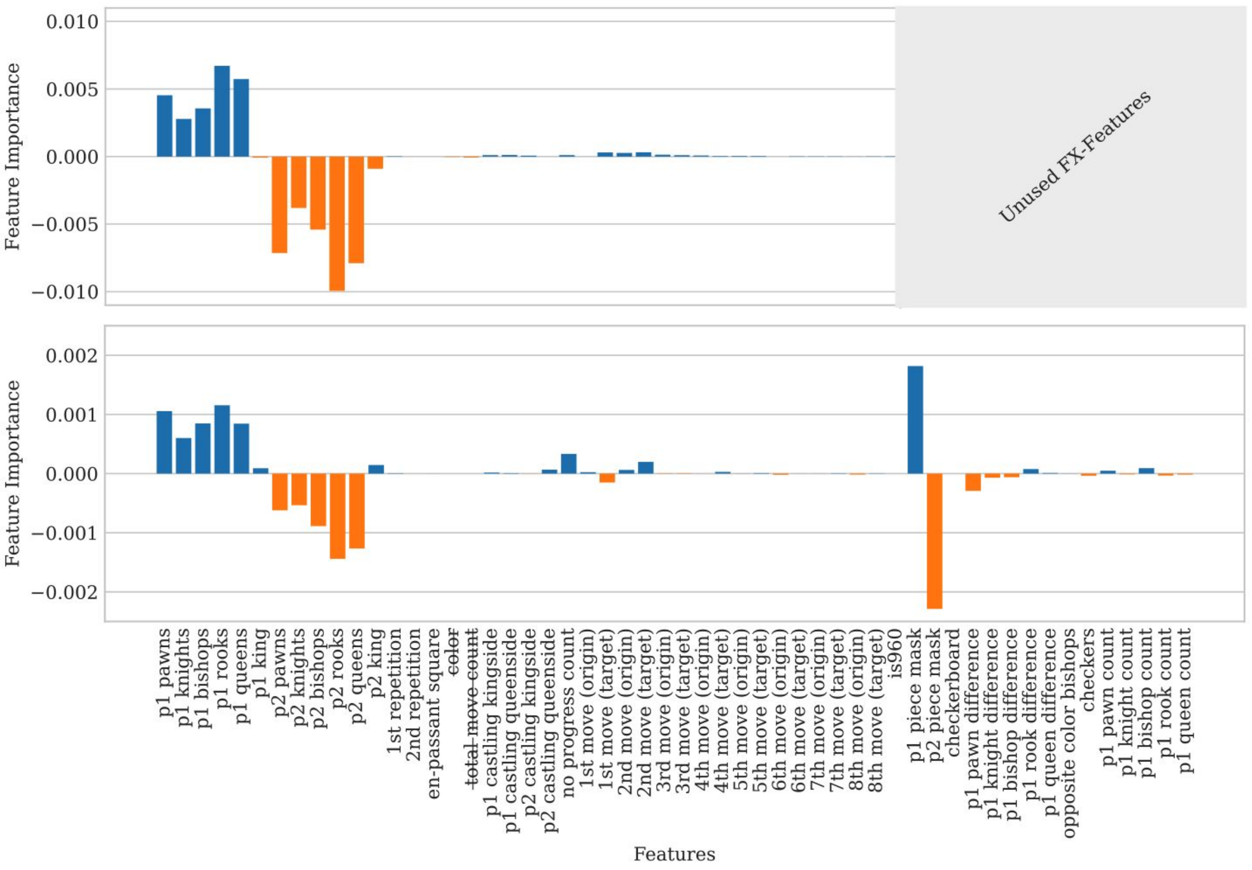
3: https://archive.org/details/KingBaseLite2019

# Results: Playing Strength




- The Feature eXtended (FX) versions beat the standard version by up to 180 Elo points
- The AlphaVile-normal version beats AlphaZero by about 30 Elo
- The classical ViT version lacks behind by the other versions

# Feature Extension: The Importance of Representation




- Measuring feature importance using Integrated Gradient (IG) method
  - measured with respect to value

- Newly added features show significant usage
  - especially player 1 & 2 piece masks

- p1 pieces show positive attribution while p2 pieces have negative impact
  - exception: king piece

# Feature Extension: Opposite Color Bishop Endgames

| FEN | Ground Truth | Net Eval | Abs. Net Eval | FX-Net Eval | Abs. FX-Net Eval |
|---|---|---|---|---|---|
| 8/2k1b3/2P5/3KP2B/8/8/8/8 w - - 0 56 | DRAW | 0.3332 | 0.3332 | **0.2025** | **0.2025** |
| 8/3k4/8/2pK4/8/4b1p1/8/5B2 w - - 0 56 | DRAW | −0.4940 | 0.4940 | **-0.2304** | **0.2304** |
| 5k2/8/8/7p/1b1p4/8/B7/5K2 b - - 0 56 | DRAW | 0.4385 | 0.4385 | **0.2500** | **0.2500** |
| 8/2b1k3/8/1B1PP3/3K4/8/8/8 w - - 0 56 | DRAW | **0.4313** | **0.4313** | 0.4561 | 0.4561 |
| 8/2k5/4Bp2/2b1p1p1/4K2p/7P/8/8 b - - 0 56 | DRAW | **0.1648** | **0.1648** | 0.2121 | 0.2121 |
| 8/8/8/5B2/1p3b2/2k1p3/8/5K2 w - - 0 56 | DRAW | −0.6412 | 0.6412 | **-0.4157** | **0.4157** |
| 8/3k4/p2P4/2P4p/2bB4/P6P/5K2/8 w - - 0 56 | DRAW | **0.3874** | **0.3874** | 0.4465 | 0.4465 |
| 7b/4k2P/6K1/2p2P2/7P/1B6/8/8 b - - 0 56 | DRAW | −0.6286 | 0.6286 | **-0.6233** | **0.6233** |
| 4k2b/7P/5PK1/7P/8/1B6/8/8 w - - 0 56 | DRAW | **0.7649** | **0.7649** | 0.8562 | 0.8562 |
| 8/5pK1/4k3/6B1/5PbP/6P1/8/8 b - - 0 56 | DRAW | −0.4810 | 0.4810 | **-0.4294** | **0.4294** |
| 2r3k1/5ppp/p7/5q2/3P4/b2B2P1/P1R2P1P/5QK1 b - - 0 56 | DRAW | **-0.5099** | **0.5099** | −0.5594 | 0.5594 |
| 5k2/5pp1/p6p/5B2/3P4/6P1/P3KP1P/2b5 w - - 0 56 | DRAW | **0.3222** | **0.3222** | 0.4718 | 0.4718 |
| 3b4/p4B1p/8/6k1/6P1/8/1P3PK1/8 w - - 0 56 | DRAW | 0.2920 | 0.2920 | **0.0783** | **0.0783** |
| 6B1/4b3/7p/3Pk2P/6PP/7K/8/8 w - - 0 56 | DRAW | **0.4867** | **0.4867** | 0.5590 | 0.5590 |
| 8/8/8/7p/2p5/5K1k/2Bb4/8 w - - 0 56 | DRAW | −0.3318 | 0.3318 | **-0.1916** | **0.1916** |
| 3R4/4BK1k/r5p1/2P2bP1/8/8/8/8 w - - 0 56 | WHITE WIN | 0.8304 | 0.8304 | **0.8714** | **0.8714** |
| 8/2k1b3/2P5/3K1P1B/8/8/8/8 w - - 0 56 | WHITE WIN | **0.4072** | **0.4072** | 0.3321 | 0.3321 |
| 3k1b2/8/3PP3/1B1K4/8/8/8/8 w - - 0 56 | WHITE WIN | 0.7121 | 0.7121 | **0.8229** | **0.8229** |
| 8/2k5/2P1K3/6p1/5p2/2b2B1P/6P1/8 b - - 0 56 | WHITE WIN | **-0.2412** | **0.2412** | −0.1441 | 0.1441 |
| 8/8/4b1p1/2Bp3p/5P1P/1pK1Pk2/8/8 b - - 0 56 | BLACK WIN | 0.4053 | 0.4053 | **0.4225** | **0.4225** |
| Mean values for draws ↓ | 0 | | 0.4472 | | **0.3988** |
| Mean values for wins ↑ | 1 | | **0.5192** | | 0.5186 |

- Our new feature representation improves the evaluation of opposite color bishop endgames.

# Summary and Future Work

- **Contributions**
  - **(Q1) Is the combination of AlphaZero with Vision Transformers beneficial in the game of chess?**
    Yes, convolutional-transformer hybrid architectures can be beneficial if efficient modules are used.
  - **(Q2) How important is the input and output representation for AlphaZero?**
    It plays a significant role in chess as it can help to offload work for the neural network, such as current material information.

**Code, Paper**

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## Future Work

- Find better features for the transformer architecture.
- Improve architecture design.


4: https://github.com/QueensGambit/CrazyAra

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