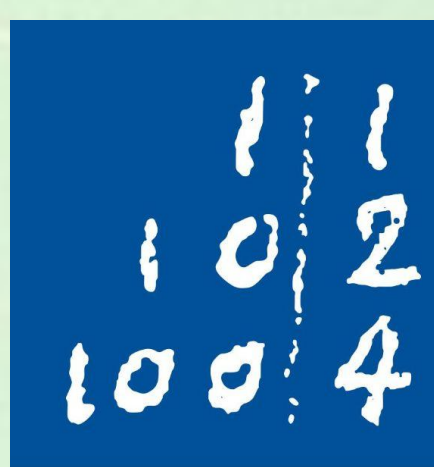


Profiling Instruction-Based bias in Language Models



Leibniz
Universität
Hannover

Author (s): Kapil Kumar Khatri & Harit Sarangi

Poster Presentations in context of "IML WiSe 2025-26" Lecture

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TL;DR

Summary

Objective: Investigate if persona instructions (e.g., "You are Conservative.") can steer the geometric gender bias of Language Models.

Method: Evaluated **BERT**, **Flan-T5**, and **Llama-3.2-1B** using Stereotype Projection (Warmth and Competence).

Result: Persona Resistance. Models didn't adopt the stance, exhibiting 3 distinct modes: **Invariance** (BERT), **Instability** (Flan-T5), and **Collapse** (Llama-1B).

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Motivation & Problem Setting

Motivation

- ❖ "System Prompts" (e.g. "You are liberal") are a standard safety mechanism, yet their internal mechanics remain opaque.
- ❖ Post-hoc Interpretability: We apply geometric projection to audit these prompts, determining if they genuinely alter the model's internal geometric representation of social groups or merely mask the output.



Problem Setting

- ❖ **Metric:** Project target terms (e.g., "Mary", "John") onto a 2D subspace defined by antonyms (*Warm-Cold*, *Competent-Incompetent*).
- ❖ **Hypothesis:**
 - **Baseline:** Standard societal bias.
 - **Conservative Persona:** Should amplify stereotypes (Women=Warm, Men=Competent).
 - **Leftist/Liberal Persona:** Should/Shouldn't diminish stereotypes.

Instructions ➡ Model ➡ Mapping

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Approach

Datasets

- ➔ **CrowS-Pairs:** Sentence-level stereotypes.
- ➔ **Population Names:** Ambiguous indicators (Mary, John).
- ➔ **Gender Terms:** Explicit indicators (Mother, Father).

Models

- ➔ **BERT-base (Control):** Encoder-only. No instruction tuning (110M).
- ➔ **Flan-T5-Base:** Encoder-Decoder (250M).
- ➔ **Llama-3.2-1B:** Decoder-only (1B).

Pipeline

Algorithm

Input Instruction

Extract Embeddings

Compute Axis

Measure Shift (Δ)

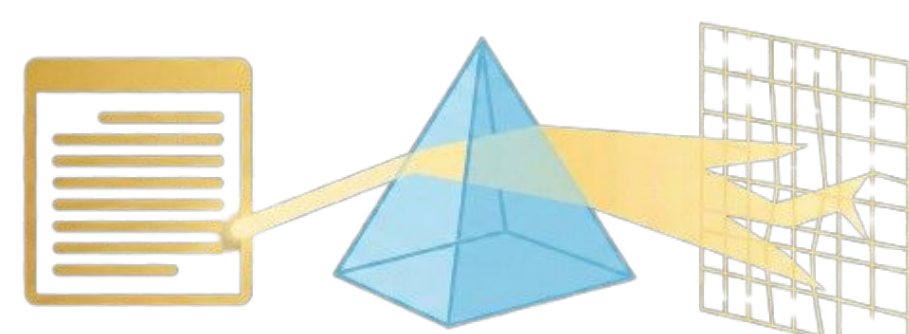
Instruction-Conditioned
Stereotype
Profiling

$$(D, M, p) \mapsto \mathcal{S}_p$$

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Future Works

- ❖ **Verify Capacity:** Test larger models (e.g. Llama-3-8B) to find the parameter threshold where instruction following stabilizes.
- ❖ **Activation Steering:** Replace text prompts with Steering Vectors that means injecting directions directly into model layers for precise control.
- ❖ **Edge AI Safety:** Rethink safety for on device models. Since prompts fail at small scales, we need architectural guardrails.



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Key Insights

Insight A: Instruction Invariance (Dataset: Population Names)

Encoder-only models remain geometrically static. Using the Population Names dataset, BERT shows clear gender bias in the baseline. However, this distribution remains identical ($\Delta \approx 0$) under the "Conservative" instruction, confirming that the model ignores the persona entirely.

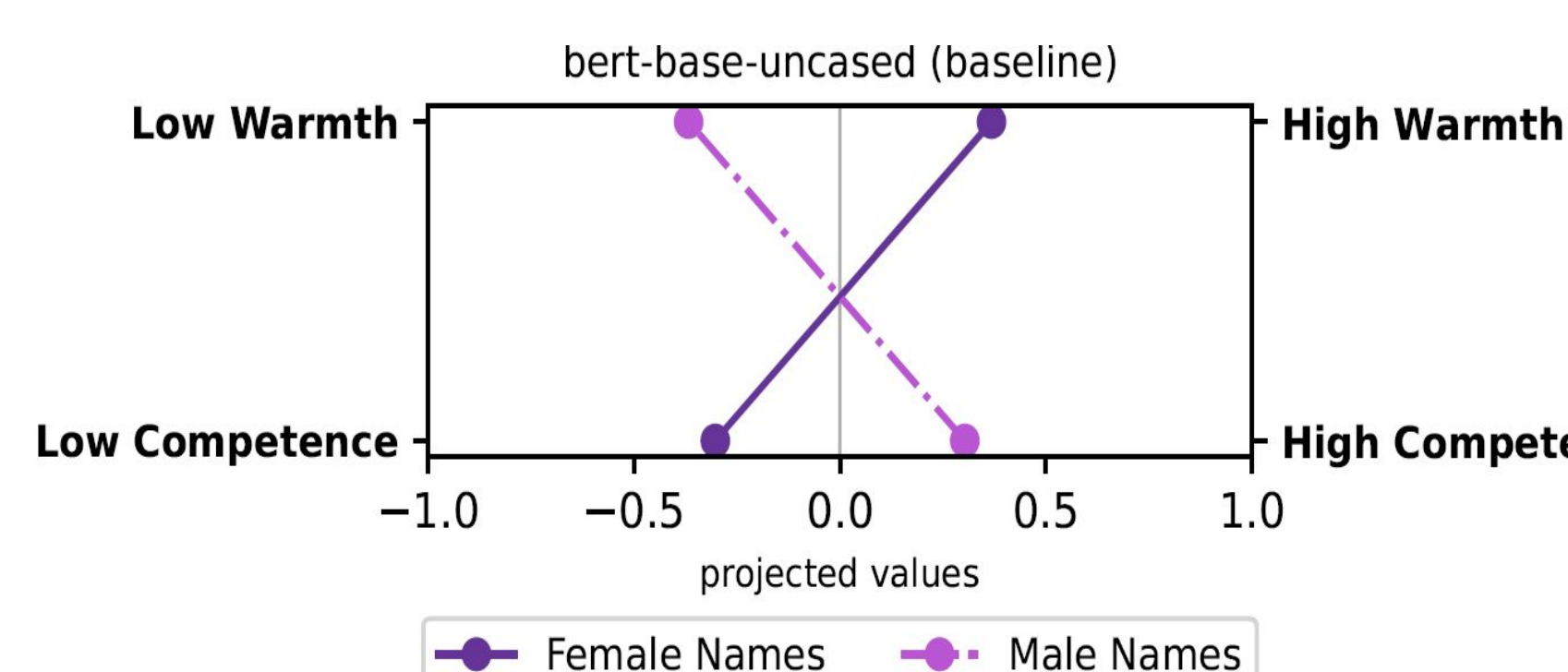


Fig 1a: Baseline (Distinct Gender Separation)

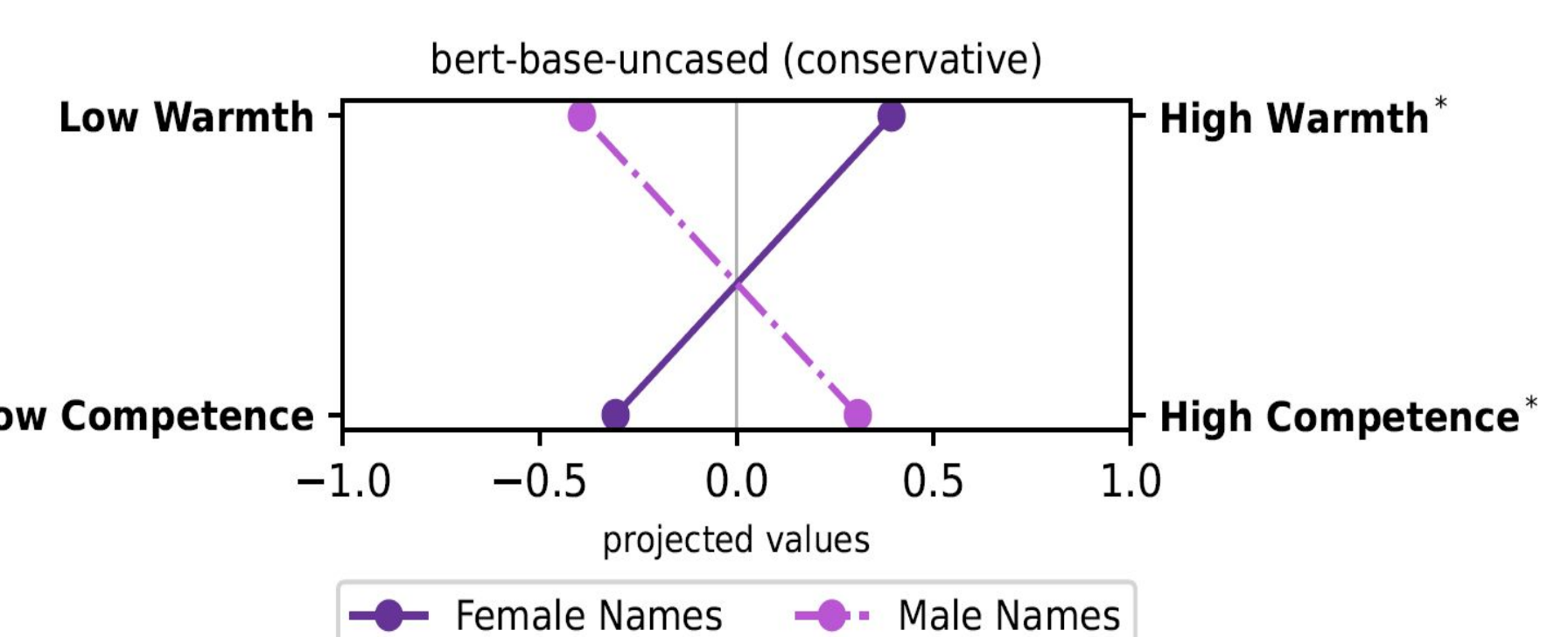


Fig 1b: Conservative (Identical Distribution - No Shift)

Insight B: Contextual Washout (Dataset: CrowS-Pairs)

Instruction tuning induces instability in complex contexts. On the **CrowS-Pairs** dataset (sentence-level stereotypes), Flan-T5 exhibits a distinct baseline distribution. Adding the persona instruction causes these complex associations to "wash out," collapsing the projection rather than steering it ideologically.

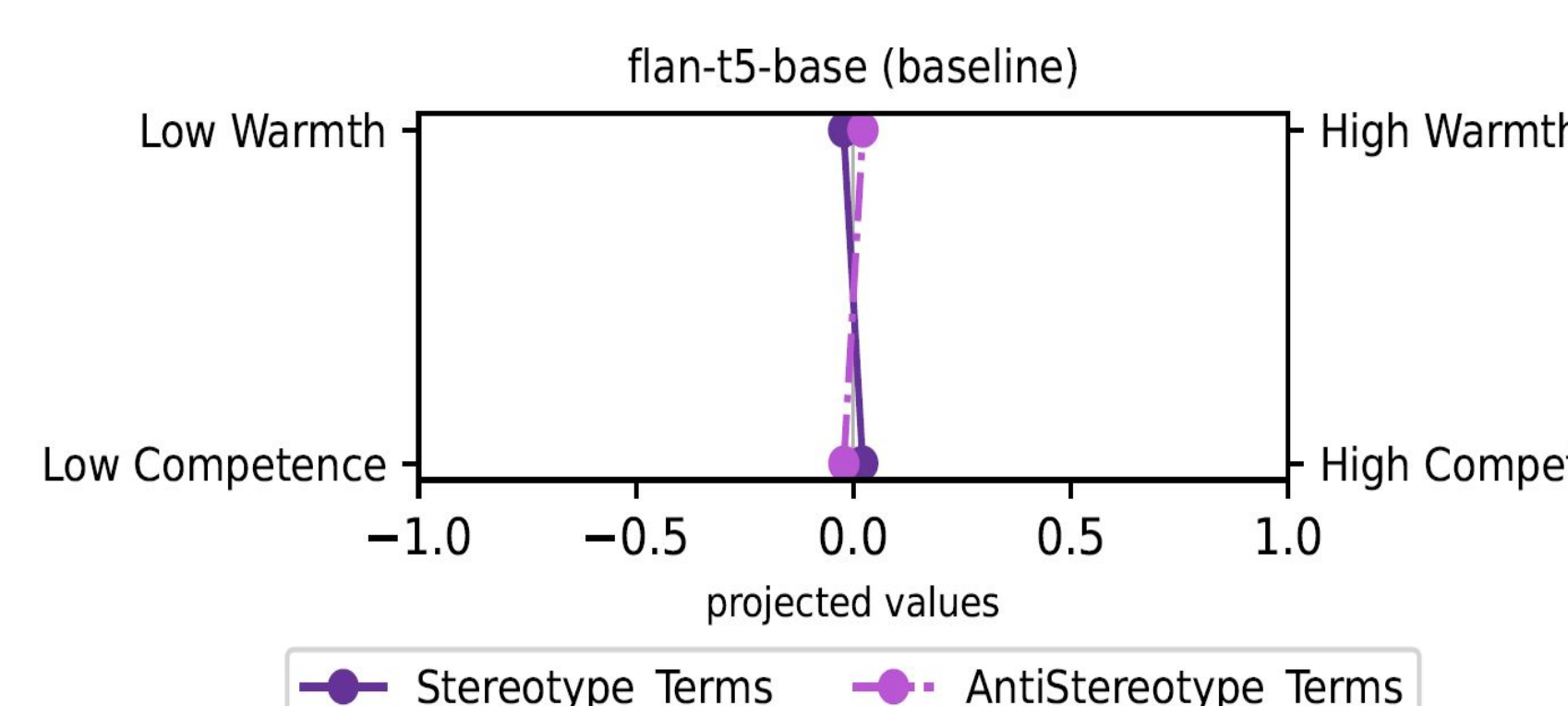


Fig 2a: Baseline (Structured Stereotype Alignment)

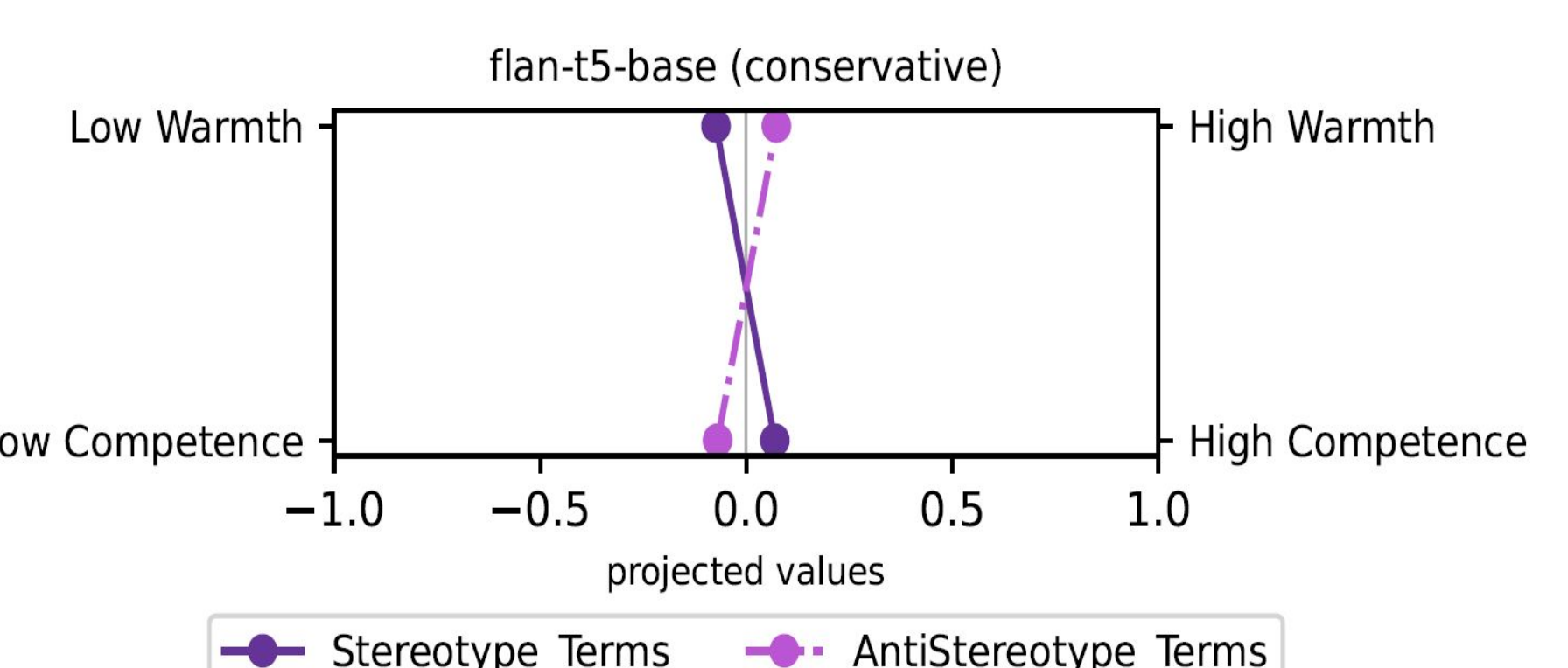


Fig 2b: Conservative (Loss of Distinct Grouping)

Insight C: Representational Collapse (Dataset: Gender Terms)

System prompts overwhelm semantic capacity. We tested **Llama-1B** on basic **Gender Terms** (e.g. "Mother", "Father"). While the baseline differentiates them clearly, the instruction prompt dominates the latent space, causing the model to lose even these fundamental semantic distinctions ($\text{Bias} \rightarrow 0.0$).

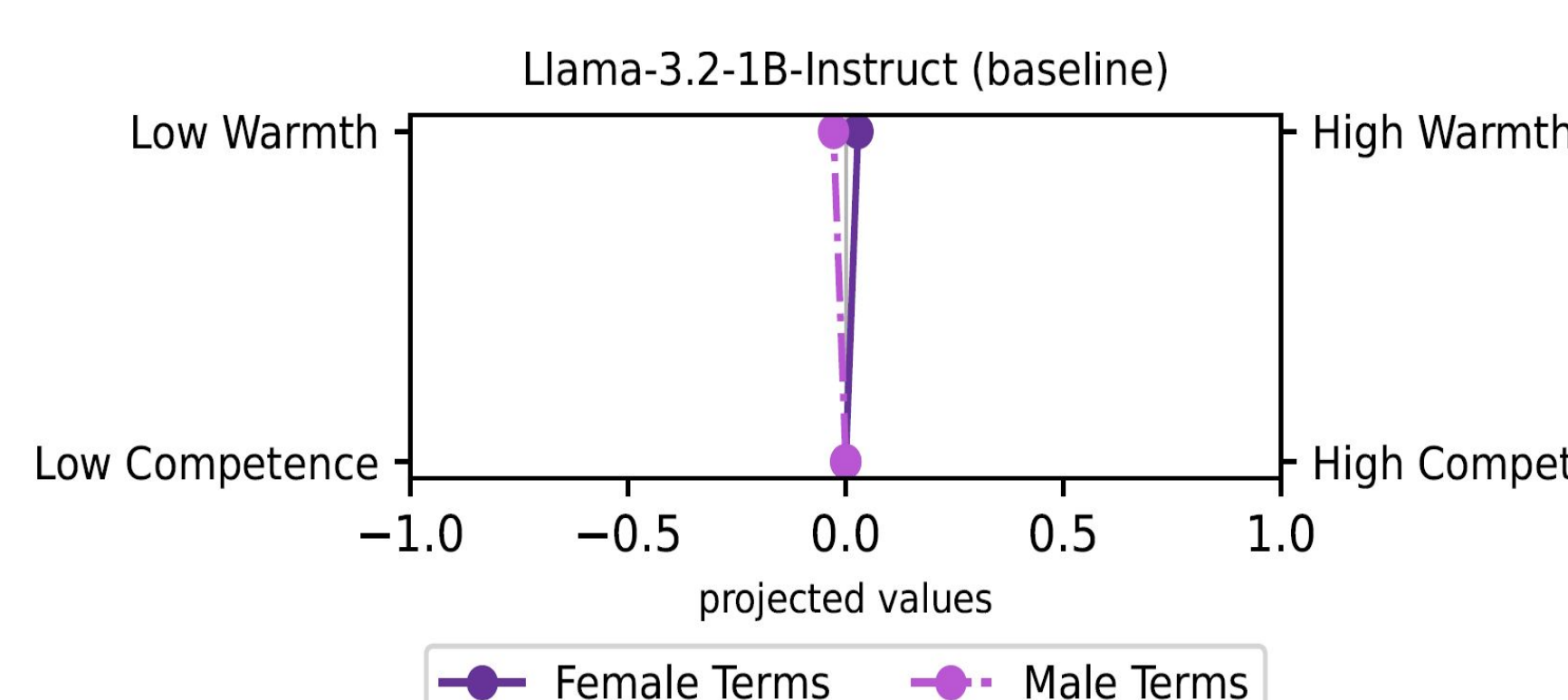


Fig 3a: Baseline (Clear Semantic Distinctions)

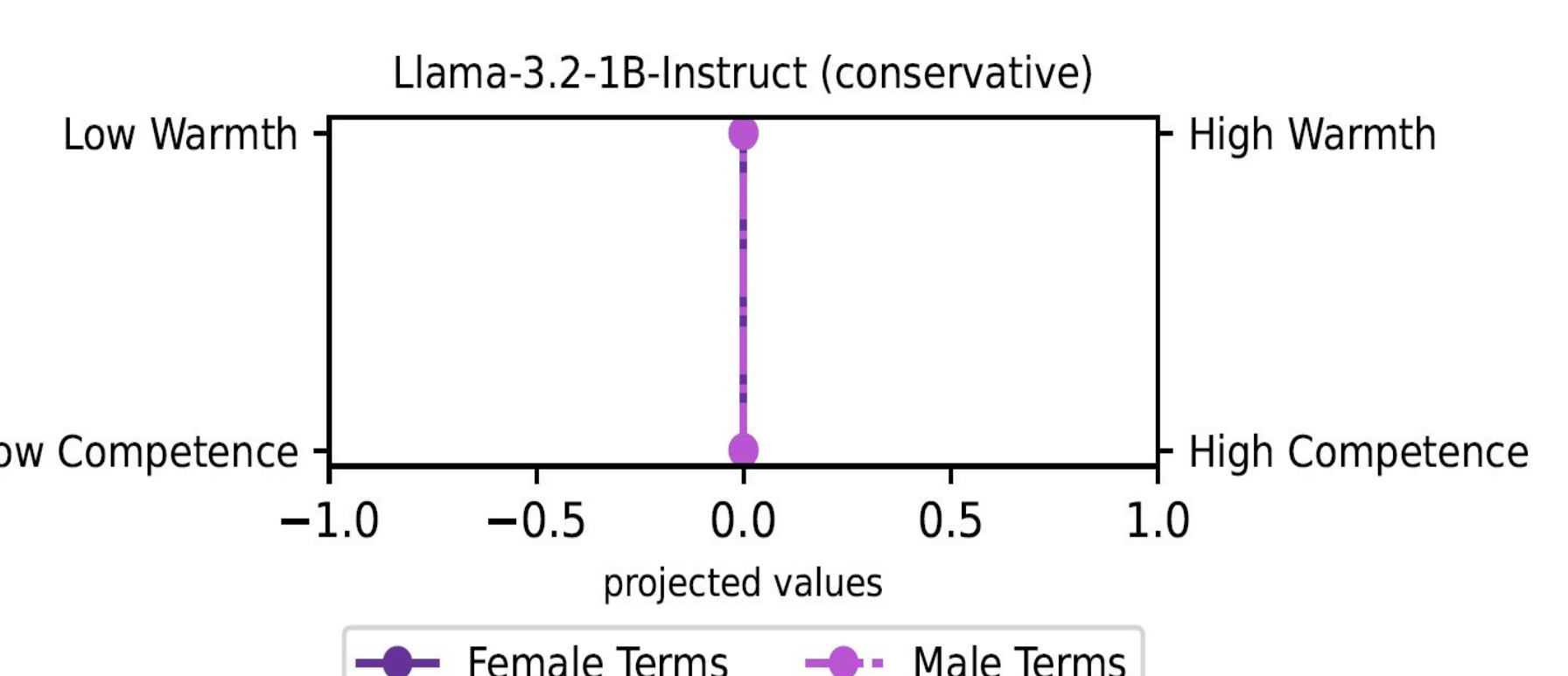


Fig 3b: Conservative (Projection Converges to Zero)