

# ShZZaM: An LLM+ATP Natural Language to Logic Translator

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## Abstract

This paper describes the ShZZaM tool that uses Large Language Models (LLMs) and Automated Theorem Proving (ATP) tools to translate natural language to typed first-order logic in the TFF syntax of the TPTP World.

Large Language Models (LLMs) (Peykani et al. 2025) have shown themselves to be useful in a broad range of applications (Sajjadi Mohammadabadi et al. 2025). However, it is well known that LLMs make mistakes (Huang et al. 2025), and this is acknowledged on LLMs’ web interfaces, e.g., ChatGPT admits “ChatGPT can make mistakes. Check important info”. In the face of such unreliability, the results from LLMs in mission-critical applications require verification. One approach is to translate the LLM input and output to a logical form that can be checked using Automated Theorem Proving (ATP) tools, e.g., (Yang et al. 2025; Cheng et al. 2025).<sup>1</sup> A key step in this verification pipeline is the faithful translation of the natural language to an appropriate logical form. This task is difficult due to the ambiguous nature of natural language statements, especially informally expressed statements. Work in this area includes LINC (Olausson et al. 2023), FOLIO (Han et al. 2024), and LINA (Li et al. 2024). This paper makes another contribution in this area, taking a new interactive approach to the translation process, zigzagging (hence the ‘ZZ’ in the tool name) between natural language and logic until convergence is achieved. A key feature of ShZZaM is its use of LLMs and Automated Theorem Proving (ATP) tools, which complement each other in the translation steps.

Figure 1 shows the overall process implemented of ShZZaM. Starting with the natural language, a combination of LLMs and ATP tools make a first translation (LLM-L+ATP - a “Zig”) to the typed first-order logic in the TFF syntax (Sutcliffe et al. 2012; Blanchette and Paskevich 2013) of the TPTP World (Sutcliffe 2024). An LLM is then used to translate the logic back to natural language (LLM-NL -

a “Zag”). An LLM is then used to judge (LLM-S) the similarity in meaning of the new and previous natural language statements. If they are adequately similar - above a “convergence threshold”, the logic inbetween them is accepted as the translation. This zigzagging continues until the natural language pairs converge to the required level of similarity (or a limit is reached). Upon convergence the logic is sent to an ATP system via the SystemOnTPTP service (Sutcliffe 2000), either a model finder if there are only axioms in the logic, or a theorem prover if there is also a conjecture. The results from the ATP system is reported in the SZS format (Sutcliffe 2008). If the similarity between the final natural language and the original natural language (which is computed in the zigzag step - see below) is above the “zigzagging threshold” the translation is complete. Otherwise the entire process repeats (or a limit is reached). This outermost loop ensures the final natural language of the converged pair is adequately similar in meaning to the original natural language.

The translation from natural language to TFF logic and back to natural language - one zigzag, is an iterative one involving LLMs and ATP tools. Figure 2 shows the details. LLM-L is used to translate from natural language to logic. The translation is successively checked using ATP tools for syntax errors and type errors (recall the logic is *typed* first-order logic). If an error occurs in either check the error message is captured and passed back into the LLM-L for another attempt. When a syntactically and type correct logic is created, LLM-NL translates the logic back to the provisional natural language, and LLM-S is used to compare this to the original natural language. If the similarity is below an “acceptance threshold” the provisional natural language is rejected and the error is passed back into the LLM-L for another attempt. This prevents the new natural language straying too far in meaning from the original natural language. If the similarity is below the acceptance threshold the provisional natural language becomes the accepted result of the zigzag. It is this accepted natural language that is compared to the previous natural language for convergence, as explained above.

The LLM translation from natural language to logic and back again works because the LLM has been exposed to enough natural language and enough TPTP format TFF logic. The former is the natural result of scraping the world’s

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<sup>1</sup>For a more comprehensive survey, just ask your favourite LLM to “show me some research on how LLMs make mistakes, and the need for symbolic checking of LLM output”.

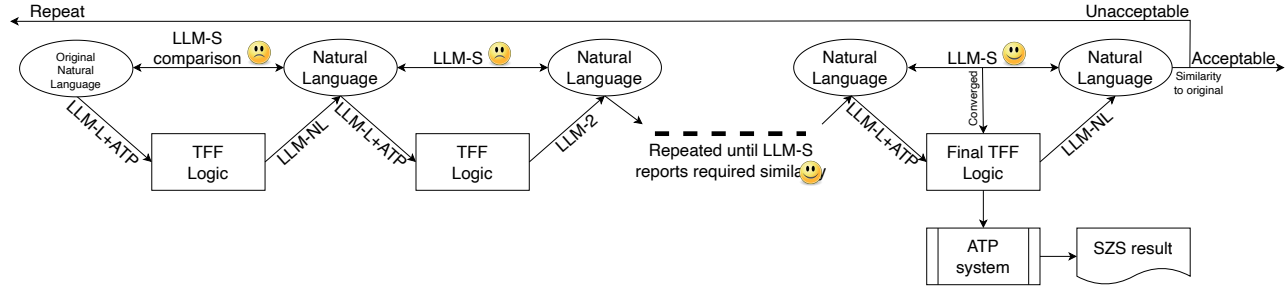


Figure 1: ShZZaM process

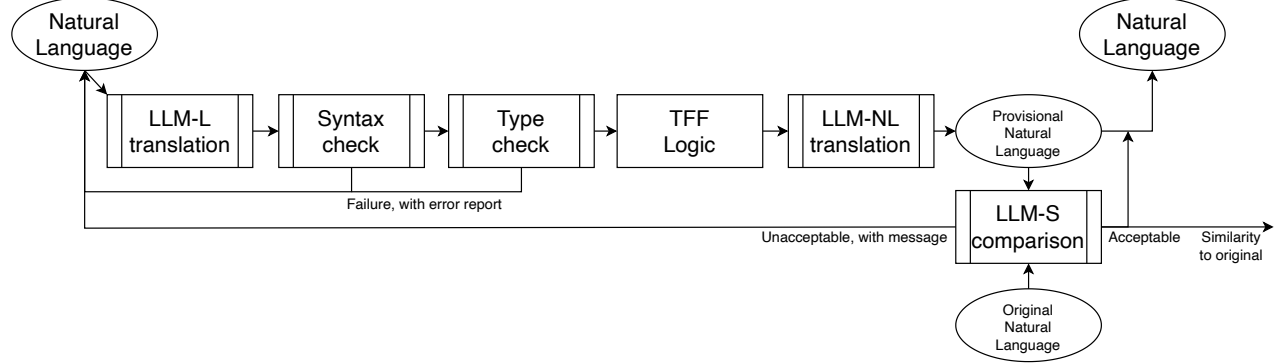


Figure 2: Details of one zigzag

web sites, etc. The latter might be surprising, as TFF is a comparatively small fragment of the data used to train LLM models. Evidently there are adequate corpora that use TFF that are exposed on the web, e.g., the TPTP problem library (Sutcliffe 2017), exports from the Isabelle Archive of Formal Proofs (Blanchette et al. 2015), exports of the Mizar Mathematical Library (Urban 2003), etc.

ShZZaM is implemented in Python.<sup>2</sup> ShZZaM has parameters that allow the selection of LLMs (default OpenAI’s gpt-5-chat-latest) and ATP systems (default Vampire (Bártek et al. 2025) for both theorem proving and model finding), setting the acceptance, convergence, and sequence thresholds (defaults 0.74, 0.94, 0.94), impose limits on the number of failures in a Zig (default 10), the number of zigzags in a sequence (default 10), and the number of sequence repetitions (default 3).

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<sup>2</sup>Available, with test files, from <https://github.com/GeoffisPapers/ShZZaM>.

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