**Code Generation Results Summary**

**Part 1. SLMs without fine-tuning**   
January 25, 2024

1. **Code used to generate the below results**

Code: <https://github.com/agnedil/code-generation>

1. **Challenges**

* The Replicate API library would not work directly, so I had to use its version within another library – LangChain.
* I used the code from this repo for HumanEval evaluation of all models: <https://github.com/openai/human-eval>. The multiprocessing module executed with an error: "AttributeError: Can't pickle local object in Multiprocessing". **I had to modify the original code to fix it**.
* The final check of the code correctness in the original OpenAI code is done by combining the problem (otherwise called starter code or function docstring) and completion: **problem["prompt"] + completion** which means the completion shouldn’t contain the problem. Two issues: 1) incorrect indentation when joining the problem and completion – the code generates error when running, 2) some models may still misunderstand and include the problem into the completion (Llama 3 Instruct trained for chat, does it for 33% of cases). Therefore, I am using an additional prompt to ask LLMs to **include the problem definition (function docstring) into the completion**, and I exclude **problem["prompt"]** from the evaluated string. **I had to modify** [**the original code**](https://github.com/agnedil/Praxis) **to fix this**.
* **Summary of code modifications** (all in execution.py):
  + **Add class DillProcess** to fix the pickling issue (uses dill instead of pickle).
  + **Modify function check\_correctness()** to have an extra argument use\_prompt which controls the exclusion or addition of problem["prompt"] to the Python program to be run. The body of the function is modified to accommodate for the use of use\_prompt.
  + Modify exception handling to **add error tracebacks** (helps when the error message is empty).
* SLMs tend to output **additional explanations** and clarifications like: “Here is the requested code completion:” etc. which break the automatic code execution during the verification stage. Adding more specific instructions like: “Complete the following code. Output only the runnable code and nothing else:” would still lead to non-runnable content like triple backticks in the output. As a result – **I had to provide minimum help to some models** by removing the initial or trailing triple backticks or strings like “```python”. Or by adding “from typing import List” as this was removed in the process (when LLM forgets to include it into the repeated func definition)
* **General approach to evaluate all models**: create one extensive and comprehensive prompt for all models. If any model fails to fully understand it and outputs code with human phrases or non-runnable symbols, it should be considered the drawback of the model.

1. **Results**

* **Llama 3 8B** – promising results.
* Non-chat optimized model ”**meta/meta-llama-3-8b**” - several cases of hallucinations when functions are repeated and the code is incomplete in the end (stops at the middle of a function). See Appendix
* **Nous-hermes-2-solar-10.7b** – tries to explain the solution if no prompt is used (func docstring as prompt) – not runnable. 25.61% when using a prompt.
* **Gemma 7B** – incomprehensible output whether I include the prompt prefix or not.
* **Code Gemma 7b IT** (when asked to output the full func for HumanEval) – a) code generation template (per HG docs): unusable output – patchy pieces of code, sometimes 1 or 2 random lines, b) chat generation template: more usable output, but still a lot of errors in the first 5 problems: repeats def in the end, 2 out of 3 outputs were completions w/out func signature and docstring, 2 others contained extraneous text, e.g. the word “def” after the func was already provided, etc. Decided not to waste compute units – the leaderboard performance is still only 55%.
* **Phixtral** – generates code, but contains extraneous text (Here is a solution). If I do additional post-processing, this will be a disadvantage for other models. Also, it is very slow – up to 2 minutes per test case (5 hours for the entire run)
* **GPT-J-6B** – not fit for the task as the model is too weak, outputs hallucinations that remind of the expected output only very remotely (trained in 2021).
* **Yi-6B** is a bilingual (Chinese) model – pass@1 = 3% if not using prompt (function docstring as prompt), otherwise if using a prompt the model outputs some irrelevant snippets of code and. Asking to output the starter code concatenated with the completion doesn’t help – the output still includes the completion without the beginning in most cases (<https://huggingface.co/01-ai/Yi-6B> ).
* **Flan-T5** outputs complete nonsense that resembles code – completely not runnable.
* **Phi** – not designed for code completion. Outputs incomprehensible combinations of letters (“em”, “emlen”, “A”, “A.A.A.A.”, etc.) as generated code with or without a prompt (if with prompt, the model repeats the entire prompt before the incomprehensible output).
* **Phixtral-2x2\_8** – MoE of two Phi models (4.5B), follows the instruction much better than Phi, reached Pass@1 = ~15%. Still outputs irrelevant human-like output although asked specifically not to do that: e.g. here’s the code, here’s the concatenated code, etc. Also, it takes ~1 min per API call which is a lot, considering there are 500 data points in the MBPP dataset.
* **Qwen1.5-7b** (replicate.com) – demonstrated a good result on HumanEval Pass@1 at ~44%, but only 20% on MBPP. The main challenge with this model is that it takes 200-300 s per one API call - took 1 day to run MBPP on replicate. This is unacceptable for experiments with agents as I will have to make several API calls per one agent call + run this for all 500 MBPP data points again – will take more than a day per experiment.
* **Mistral 7B** provided the expected result. The model would strip any docstrings from the functions – only the definition def was left. I helped the model by removing triple backticks from start / end, “```python”, and adding “from typing import List” because the model would strip this import most of the times while the import is specific to the HumanEval dataset.
* **Codestral Mamba** – showed the best result on my leaderboard, followed by **Ministral 8B** and, surprisingly, **Ministral 3B**. The latter is the smallest model that I tried, but it outperformed many other models that are 2 to 2.5 times bigger, and even the models with 22B parameters (7+ times bigger). Other models from the Mistral family also showed good results which, on average, make this group of models as the leading one among all other models.
* **OpenCodeInterpreter-DS-6.7B** and **Artigenz-Coder-DS-6.7B** – when asked to output the entire function, keeps saying “Here is the completed function” (even if I ask not to do it in the prompt). Model needs extra help by getting the code placed between *```python* and *```*. **May be better at pure code completion**?
* **Mamba 2.8B (**replicate.com): if not using a prompt (func docstring as prompt) – the model tries to generate a completion, but then follows a paragraph of hallucinations that look like human free-form text with how-to questions about software development. When using a prompt – the model doesn’t even try to complete the code – it starts hallucinating right away (see saved file with examples).
* Gemma 7B, Gemma 2B, Flan-T5, Phi, Mamba 2.8B (replicate.com) – incoherent output.
* **Deepseek-Coder-6.7B-Instruct** – scored great on HumanEval, but *did only 1% on MBPP*, mainly because the model outputs unnecessary explanations, although it is explicitly asked not to do that. Example: “Sure, here is the Python function that calculates.” This is done for every data point. Somewhat similar numbers are for OpenCodeInterpreter-DS-6.7B. Reason is same: unnecessary clarifications when asked not to do it: “Here is the Python function that satisfies the given tests:” *Solution – maybe decrease temperature*?
* **Llama 3**.1 8B Instruct – released fall 2024. Inference takes an average of 2 minutes for Human Eval and 0.75 min for MBPP. Both tasks required 4 hours to finish running in Google Colab on an A100 GPU which is the best available. This may be too long for subsequent experiments, but I was able to get this model work for the Reflection workflow – **TODO: add timer for the entire notebook**.
* **Phixtral** on Replicate – takes 100 to 200 seconds per API call. Running this model for Big Code Bench (500 data points) took well all night and up to the lunch time of the next day. Considering that the results from this model are very low in general, I will discontinue using it for agent experiments as they will take even more time due to several API calls per iteration. Maybe use the HuggingFace version of the model? What if the HF version is more up-to-date and faster?
* **NxCode is** not only one of the best models quality-wise, but it also ran much faster than the models that started at the same time or even earlier (as measured on plain agent on MBPP) – OpenCodeInterpreter was considerably slower while Artigenz was the slowest - twice as slow (and one of the worst quality-wise). Llama is also relatively fast – it finished after NxCode, but before OpenCodeInterpreter. Another slow model – DeepseekCoder which was twice as slow as CodeQwen. Code Gemma ran even faster than CodeQwen.

All models received slight help by stripping ``` backticks at edges including the ```python string + adding “from typing import List” which is often stripped by SLMs.

The pass@1 scores below are provided for my run (first number) and then for the result shown on the Big Code Leaderboard (second number), if it is available: <https://huggingface.co/spaces/bigcode/bigcode-models-leaderboard>

***Table 1. Pass@1 Score for Testing SLMs on Multiple Datasets***

| **Model** | **Hosted By** | **Model Size** | **Human-Eval Full Func** (Me / Big Code) | **H-E Compl** | **MBPP** | **LBPP** | **Big Code Bench** | **Rank** | **Temp / top\_p** | **Cost $, full func** | **Notes** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Small Language Models (SLMs)** | | | | | | | | | | | |
| Nxcode-CQ-7B-orpo | Google Colab | 7.25B | 82.93 / 87.23 | 75.61% | 73% | 22.84% | 24% | 1 | 1.0 / 1.0 | $50/month |  |
| Codestral Mamba | mistral.ai | 7.3B | 75.61% / 75% | 60.37% | 39.4% | 26.54% | 23% | 3 | 0.7 / 1.0 | 0.02 |  |
| Ministral 8B | mistral.ai | 8B | 72.56% / 76.8% (instruct) | 71.34% | 56.2% | 22.22% | 24.6 | 2 | 0.3 / 1.0 | 0.01 |  |
| Deepseek-Coder-6.7B-Instruct | Google Colab |  | 65.24% / 80.22% | 70.73% | 1% | 0% (extra words!) | 32.2% | 9 | 1.0 / 1.0 | $50/m |  |
| Ministral 3B | mistral.ai | 3B | 64.63% / 77.4% (instruct) | 61.59% / 77.4% (instruct) | 51.8% | 20.99% | 26.8% | 5 | 0.3 / 1.0 | 0.01 |  |
| Mistral-Nemo-Instruct-2407 | mistral.ai | 12B | 58.54%/ 67% | 53.05% | 47.4% | 21.6% | 17.2% | 7 | 0.3 / 1.0 | 0.01 |  |
| Llama 3.1 8B Instruct | Google Colab | 8B | 65.9% / 72.6% | 55.47% | 56.8% | 21.6% | 29.8% | 4 |  |  |  |
| CodeQwen1.5-7B-Chat | Google Colab |  | 50% / 87.2% | 54.88% | 55.2% | 19.75% | 26.8% | 6 | 1.0 / 1.0 | $50/m |  |
| OpenCodeInterpreter-DS-6.7B | Google Colab |  | 41% / 73.2% | 71.95 / 73.2% | 5.4% | 8% | 32.2% | 8 | 1.0 / 1.0 | $50/m |  |
| Mistral 7B, open-mistral-7b | mistral.ai | 7B | 31.1% / 30.5% | 35.98% / 30.5% | 13.6% | 9.9% | 15.6% | 11 | 0.7 / 1.0 | 0.01 |  |
| Nous-hermes-2-solar-10.7b | replicate.com | 10.7B | 25.61% | 28.65% | 30.4% | 8% | 43.4% | 10 | 0.95 / 1 | 0.61 |  |
| Phixtral-2x2\_8 (4.5B) | replicate.com | 4.5B | 14.64% | 34.756% | 14.6% | 4.9 | 20.6% | 14 | 0.95 / 1 | 2.77 |  |
| Artigenz-Coder-DS-6.7B | Google Colab |  | 1.22% / 70.89% | 73.17% | 0.2% | 4.32% | 13.4% | 13 | 1.0 / 1.0 | $50/m. |  |
| Code Gemma 7b IT | Google Colab | 7B | 0% (? model) | 27.44% | 51% (chat model) | 19.14% (chat model) | 2.4% | 12 | 1.0 / 1.0 |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |
| **Slightly Bigger SLMs** | | | | | | | | | | | |
| Mistral-Small-2409 | mistral.ai | 22B | 70.73% / 80% | 64.63% | 60.2% | 25.3% | 20.6% |  | 0.7 / 1.0 | 0.03 |  |
| Codestral latest | mistral.ai | 22.2B | 26.83% / 81.1% | 64.63% | 37% | 48.15 | 12.8% |  | 0.7 / 1.0 | 0.15 |  |
| Mixtral-8x7B-v0.1 | mistral.ai | 12B active (47B total) | 16.46% / 40.2% | 33.54% | 0% | 5.6% | 11.8% |  | 0.7 / 1.0 | 0.05 |  |
|  |  |  |  |  |  |  |  |  |  |  |  |
| **Not Useful SLMs** | | | | | | | | | | | |
| Qwen1.5-7b | replicate.com | 7B | 43.9% | 200 s per API call | 19.4% | 200 s per API call | 200 s API call | 200 s API call | 0.95 / 1 | 3.55 |  |
| Llama 3 8B | Replicate | 8B | 51.83% / 45.65% | API Error | API Error | API Error | API Error |  | 0.95 / 1 | 0.29 |  |
| Yi 6B | replicate.com | 6B | 3% | 3% | 0.2% |  |  |  | 0.95 / 1 | 0.44 |  |
| Gemma 7B | replicate.com | 7B | 0 % | 0% | 0% |  |  | 0% | 0.95 / 1 | 0.05 |  |
| Gemma 2B | replicate.com | 2B | 0 % | 4.26% | 4.6% |  |  |  | 0.95 / 1 | 0.05 |  |
| Flan-T5 | replicate.com |  | 0% |  |  |  |  |  | 0.95 / 1 |  |  |
| Phi-2 | replicate.com |  | 0% | Incoherent (even if temp=0.25 |  |  |  |  | 0.95 / 1 |  |  |
| Mamba 2.8B | replicate.com | 2.8B | n/a | Incoherent (even if temp=0.25 | 0% |  |  | 0 | 0.95 / 1 | 0.02 (20 calls) |  |
|  |  |  |  |  |  |  |  |  |  |  |  |

**Notes**

1. The second number in the HumanEval Full Funk column is the performance of a model on the HuggingFace’s Big Code Models Leaderboard (<https://huggingface.co/spaces/bigcode/bigcode-models-leaderboard>) – not to be confused with the Big Code Benchmark dataset because HuggingFace presents only the humanEval results in its leaderboard.
2. HuggingFace transformer models’ default temperature and top\_p parameters are explained here: <https://huggingface.co/docs/transformers/v4.22.2/en/main_classes/text_generation>. Usually they are 1.0 and 1.0, respectively, and can be checked by running model.config.temperature and model.config.top\_p.

***Table 2. Model Versions (Table Composed on January 25, 2025)***

| **Model** | **Hosted By** | **Model Size** | **Model Version** |
| --- | --- | --- | --- |
| NTQAI/Nxcode-CQ-7B-orpo | Google Colab | 7.25B | Model version as seen on <https://huggingface.co/Artigenz/Artigenz-Coder-DS-6.7B/commits/main> (from model card click on **Files and Versions** and then on **History: 7 commits** (3 commits may be different)):  74f3b3c06de36b261af9ef857279d6e33f893336, **commit of May 30, 2024** |
| Codestral Mamba | mistral.ai | 7.3B | Endpoint: open-codestral-mamba. **Version: v 0.1** |
| Ministral 8B | mistral.ai | 8B | Endpoint: ministral-8b-latest. **Version: 24.10** |
| deepseek-ai/deepseek-coder-6.7b-instruct | Google Colab |  | Model version as seen on <https://huggingface.co/google/codegemma-7b-it/commits/main>):  e5d64addd26a6a1db0f9b863abf6ee3141936807, **commit of Feb 1, 2024** |
| Ministral 3B | mistral.ai | 3B | Endpoint: ministral-3b-latest. **Version: 24.10** |
| Mistral-Nemo-Instruct-2407 | mistral.ai | 12B | Endpoint: open-mistral-nemo. **Version: 24.07** |
| meta-llama/Meta-Llama-3.1-8B-Instruct | Google Colab | 8B | Model version as seen on <https://huggingface.co/google/codegemma-7b-it/commits/main>):  0e9e39f249a16976918f6564b8830bc894c89659, **commit of Sep 25, 2024** |
| Qwen/CodeQwen1.5-7B-Chat | Google Colab |  | Model version as seen on <https://huggingface.co/google/codegemma-7b-it/commits/main>):  7b0cc3380fe815e6f08fe2f80c03e05a8b1883d8, **commit of April 30, 2024** |
| m-a-p/OpenCodeInterpreter-DS-6.7B | Google Colab |  | Model version as seen on <https://huggingface.co/google/codegemma-7b-it/commits/main>):  60b89884df814590abd76757a6db4a527cbdfc91, **commit of Mar 3, 2024** |
| Mistral 7B | mistral.ai | 7B | Endpoint: open-mistral-7b. **Version: v0.3** |
| Nous-hermes-2-solar-10.7b | replicate.com | 10.7B | nateraw/nous-hermes-2-solar-10.7b:1e918ab6ffd5872c21fba21a511f344fd12ac0edff6302c9cd260395c7707ff4 (**1 year ago**) |
| Phixtral-2x2\_8 (4.5B) | replicate.com | 4.5B | lucataco/phixtral-2x2\_8:25d7b93bb0ec9e8dd94fcc69adc786759243a5628ba5574bd9609d6abafe57cf (**11 months, 2 weeks ago**) |
| Artigenz/Artigenz-Coder-DS-6.7B | Google Colab |  | Model version as seen on <https://huggingface.co/google/codegemma-7b-it/commits/main>):  a0dea4a1c6cfdef8043c8accffa803887f444f45, **commit of April 16** |
| google/codegemma-7b-it | Google Colab | 7B | Model version as seen on <https://huggingface.co/google/codegemma-7b-it/commits/main>):  078cdc51070553d1636d645c9a238f3b0914459a, **commit of Aug 7, 2024** |
| **Slightly Bigger SLMs** | | | |
| Mistral-Small-2409 | mistral.ai | 22B | Endpoint: mistral-small-latest. **Version: 24.09** |
| Codestral latest | mistral.ai | 22.2B | Endpoint: codestral-latest. **Version: 25.01** |
| Mixtral-8x7B-v0.1 | mistral.ai | 12B active (47B total) | Endpoint: open-mixtral-8x7b. **Version: v0.1** |
| **Not useful SLMs** | | | |
| Qwen1.5-7b | replicate.com | 7B | lucataco/qwen1.5-7b:f85bec5b21ba0860e0f200be6ef5af9d5a65b974b9f99e36eb036d21eab884de (**11 months, 2 weeks ago**) |
| Llama 3 8B | Replicate | 8B | No version shown on replicate.com – hence the API error |
| Yi 6B (non-chat) | replicate.com | 6B | 01-ai/yi-6b:d302e64fad6b4d85d47b3d1ed569b06107504f5717ee1ec12136987bec1e94f1 (**1 year 2 months ago**) |
| Gemma 7B | replicate.com | 7B | google-deepmind/gemma-7b:2ca65f463a2c0cfef4dbc4ba70d227ed96455ef6020c1f6983b2a4c4f3ecb4ec (**11 months ago**) |
| Gemma 2B | replicate.com | 2B | google-deepmind/gemma-2b:26b2c530f16236a4816611509730c2e6f7b27875a6d33ec5cff42961750c98d8 (**11 months ago**) |
| Flan-T5 | replicate.com |  | replicate/flan-t5-xl:eec2f71c986dfa3b7a5d842d22e1130550f015720966bec48beaae059b19ef4c (**1 year 9 months ago**) |
| Phi-2 | replicate.com |  | lucataco/phi-2:740618b0c24c0ea4ce5f49fcfef02fcd0bdd6a9f1b0c5e7c02ad78e9b3b190a6 (**11 months, 3 weeks ago**) |
| Mamba 2.8B | replicate.com | 2.8B | adirik/mamba-2.8b:571abd73203a3dd3d7071f1c0380a3502c427aba98a2fb5edf2f7cfdeea1676c (**11 months, 2 weeks ago**) |

Source of model versioning information:

1. <https://docs.mistral.ai/getting-started/models/models_overview/>
2. <https://replicate.com/explore>
3. To determine versions for HuggingFace models, see the sha hash + date for the latest commit here: from **model card** click on **Files and versions,** then click on **History: 7 commits** (# commits may be different)
4. **Analysis**

* **Nxcode-CQ-7B-orpo** stands out as the top-scoring SLM overall.
* Other strong contenders include **Ministral 8B**, **Deepseek-Coder-6.7B, and Llama 3.1**.
* Several mid-tier models (e.g., CodeQwen1.5-7B-Chat, Mistral 12B Nemo, OpenCodeInterpreter) show moderate but inconsistent performance.
* Several models fall into low or nearly unusable categories due to extremely low pass rates or major practical limitations (long latencies, API errors, or nonsense outputs).
* **Larger parameter counts** do **not** always guarantee higher pass@1!

**Top Performers**

1. **Nxcode-CQ-7B-orpo**
   * *Human-Eval pass@1*: 82.93% / 87.23% (very high)
   * Solid MBPP (~73%) and LBPP (~22–24%)
   * Overall among the highest marks on multiple benchmarks.
2. **Ministral 8B**
   * *Human-Eval pass@1*: 72.56% / 76.8%
   * MBPP around 71%, mid-50% on other tasks, overall strong.
3. **Deepseek-Coder-6.7B-Instruct**
   * *Human-Eval pass@1*: 65.24% / 80.22%
   * Does well on MBPP (~70%) but struggles on LBPP (1%).
   * Not as consistently high as Nxcode, but still a strong contender.
4. **Ministral 3B** (with “instruct” variant)
   * *Human-Eval pass@1*: up to ~64.63% / 77.4% in instruct mode
   * Fairly good MBPP (~61–77%), decent LBPP (~20–27%).
   * Punches above its parameter count.
5. **Llama 3.1 8B Instruct**
   * *Human-Eval pass@1*: ~65.9% / 72.6%
   * MBPP and LBPP in the mid 50–60% range, a respectable showing.

These top models generally exceed ~60% pass@1 on Human-Eval (sometimes well above 70–80%), plus moderate to good results on MBPP and other code tasks.

**Mid Performers**

1. **CodeQwen1.5-7B-Chat**
   * *Human-Eval pass@1*: 50% / 87.2% (unclear if the 87.2% is a different setting)
   * MBPP ~55%, LBPP ~19–26%.
   * Results are somewhat mixed but places it in a middle tier on average.
2. **Mistral-Nemo-Instruct-2407 (12B)**
   * *Human-Eval pass@1*: ~58.5% / 67%
   * MBPP ~47%, LBPP ~21–22%.
   * Decent but not top-tier.
3. **OpenCodeInterpreter-DS-6.7B**
   * *Human-Eval pass@1*: ~41% / 73.2%
   * Good MBPP (~72%), but quite low performance on some tasks like LBPP (5–8%).
4. **Mistral 7B** (open-mistral-7b)
   * *Human-Eval pass@1*: ~31%
   * MBPP ~13.6%, LBPP ~9.9%.
   * Sits lower than the ones above, but still not in the “near-zero” group.

Many of these mid-range models have partial strong points (e.g., decent MBPP or decent instruct performance) but are inconsistent across benchmarks.

**Low Performers**

A number of models show **very low** pass@1 on Human-Eval (often near 0–25%) or produce mostly irrelevant outputs:

* **Nous-hermes-2-solar-10.7b** (~25.6% Human-Eval)
* **Phixtral-2x2\_8 (4.5B)** (~14.64%)
* **Artigenz-Coder-DS-6.7B** (1.22% / 70.89% in some mode, but near 0% in others)
* **Code Gemma 7b IT** (0% on some tasks)

And several models from the “Not Useful SLMs” section with near-zero performance or major usability problems (API errors, extremely long latencies, or nonsense outputs):

* **Qwen1.5-7B** (unusable due to 200 s API calls)
* **Llama 3 8B (Replicate)** (API errors)
* **Yi 6B**, **Gemma 7B**, **Gemma 2B**, **Flan-T5**, **Phi**, **Mamba 2.8B** all show 0–3% pass@1 or produce irrelevant outputs.

1. **Summary of what was done**

* Table contains much more data now.
* Finished the **first and second HumanEval runs and the MBPP run** – CONSIDERABLE EFFORT as the dataset has 500 data points which means the code needs to be generated and verified 500 times.
* According to (Matton et al. 2024), **data leakage** in code generation occurs when popular evaluation benchmarks (like HumanEval and MBPP) appear in a model’s training data and, whether intentionally or unintentionally, compromise the validity of test scores. Therefore, two more runs were done on the **LBPP** and **Big Code Bench** dataset for all models.
* Conducted an initial experiment with the **Reflection agentic workflow**.
* Need to continue applying various agentic workflows.
* Need to finish the **Methodology** section

**References**

Matton A., Tom Sherborne, Dennis Aumiller, Elena Tommasone, Milad Alizadeh, Jingyi He, Raymond Ma, Maxime Voisin, Ellen Gilsenan-McMahon, Matthias Gallé. 2024. **On Leakage of Code Generation Evaluation Datasets**.

**Visuals**

* 1. **Pass@1 Scores Visualized by Model / Dataset**

**Figure 1**. Pass@1 Scores Visualized by Model / Dataset

* 1. **Initial Results for Models by Dataset**

A table with numbers and letters

AI-generated content may be incorrect.

**Table 1**. Initial Results for Models by Dataset

* 1. **Normalized Results with Final Ranking**

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AI-generated content may be incorrect.

**Table 2**. Normalized Results. See **Average** column for final ranks (after min max scaling).

**Next Steps**

(This was not submitted on January 25 – for my reference only)

* 1. Finish the **temperature & top\_k** experiments – decide which models to discontinue (Phixtral and Artigenx? Or more?).
  2. Finalize the format of the **Reflection workflow**: keep simple as I did with Llama 3.1 or use Langchain or another format?
  3. Run Reflection workflow for **all models all datasets**.
  4. Do 1 experiment with **another agentic workflow** (Llama?)
  5. Finish the Chapter 3 **Methodology**.

EVERYTHING ABOVE WAS SUBMITTED ON JANUARY 25, 2025. THIS IS THE LATEST REVISION OF THIS INFORMATION.

**Part 2. Agents**

* 1. **February 8, 2025 Submission**

In the last two week I did multiple runs of the plain reflection agent on 7 models across 4 datasets. Each run takes some 1 to 2 hours. Here are the current results, and I will share more insights and analysis in the coming weeks.

A table with numbers and a number in the middle

AI-generated content may be incorrect.

* 1. **February 21, 2025 Submission**

**Analysis of Errors in Plain Reflection Agents**

* **OpenCodeInterpreter-DS-6.7B** (MBPP dataset): There are some 20% of cases when the model outputs only code and nothing else. Although asked specifically in the prompt not to do this, the model often adds human-like explanations before and after the code + code fences + test cases:
  + **```python … ```**. Sometimes twice – first for the func per se, second time for a testing func or assert statements.
  + **Human-style clarifications**:
    - Here is the improved solution to the problem:
    - Here is the python function that adds pairwise for tuples:
    - The code uses the built-in `zip` function to pair the elements in the tuples. `zip` pairs the elements of the tuples in parallel
    - Here is a Python function for … It takes three parameters: an array, an integer `n`, and another integer `m`. It calculates the product of …
    - Note: This solution corrects the errors in the proposed solution and removes redundant code.
    - The proposed solution is correct and can drop empty items from a given dictionary. Here is the improved solution:
  + **Testing code**:
    - * print(tuple\_intersection([(3, 4), (5, 6), (9, 10), (4, 5)], [(5, 4), (3, 4), (6, 5), (9, 11)]))
    - **Prints this after the func’s return statement**:  
      Example 1:  
      print(find\_adverb\_position("clearly!! we can see the sky"))  
      print(find\_adverb\_position("seriously!! there are many roses"))  
      print(find\_adverb\_position("unfortunately!! sita is going to home"))  
      Example 2:  
      def upper\_ctr(s):

return sum(1 for c in s if c.isupper())

print(upper\_ctr('PYthon'))

print(upper\_ctr('BigData'))

print(upper\_ctr('program'))  
**To catch this I need to know the func name**.

* + - Simple assert statements: assert drop\_empty({'c1': 'Red', 'c2': 'Green', 'c3':None})=={'c1': 'Red', 'c2': 'Green'}. **Sometimes everything is fine (no explanations or code fences), but only the assert statements need to be removed.**
    - More complex test code:  
      def tests():

assert decimal\_to\_Octal(10) == "12"

assert decimal\_to\_Octal(2) == "2"

assert decimal\_to\_Octal(33) == "41"  
 print("All tests passed!")  
  
 Example 2:  
```python

def decimal\_to\_Octal(decimal):

return oct(decimal)[2:]

def tests():

assert decimal\_to\_Octal(10) == "12"

assert decimal\_to\_Octal(2) == "2"

assert decimal\_to\_Octal(33) == "41"

print("All tests passed!")

tests()

```  
Not sure what to do with this one. If this pattern repeates with other modes, I may introduce this case into the cleab\_code() func.

* **NxCode**
  + **Exceptional prompt following ability** – many cases when only the code outputs and nothing but the code (as asked in the prompt)
  + ```python **OR** ```python…``` - multiple cases
  + Clarifications:
    - Here is the improved solution:
  + **Testing code**:

Example 1

**assert** max\_length\_list([[0], [1, 3], [5, 7], [9, 11], [13, 15, 17]])==(3, [13, 15, 17])

**assert** max\_length\_list([[1,2,3,4,5],[1,2,3,4],[1,2,3],[1,2],[1]])==(5,[1,2,3,4,5])

**assert** max\_length\_list([[3,4,5],[6,7,8,9],[10,11,12]])==(4,[6,7,8,9])

def max\_length\_list(l1):

max\_length\_sublist = max(l1, key=lambda sublist: len(sublist))

return (len(max\_length\_sublist), max\_length\_sublist)

Example 2:

Here is the improved solution:

```python

def find\_parity(x):

x ^= x >> 1

x ^= x >> 2

x ^= x >> 4

x ^= x >> 8

x ^= x >> 16

return "Even Parity" if x & 1 else "Odd Parity"

**print(find\_parity(12))**

**print(find\_parity(7))**

**print(find\_parity(10))**

**MULTIPLE CASES OF PRINT(FUNC\_NAME(…)) ANS ASSERT STATEMENTS**

* + Wrong test logic:

EXAMPLE 1

def neg\_nos(lst):

return [i for i in lst if i < 0]

neg\_nos([-1,4,5,-6])

neg\_nos([-1,-2,3,4])

neg\_nos([-7,-6,8,9])

MISSING ASSERT KEYWORD

EXAMPLE 2

Here is the improved Python code:

```

def rectangle\_area(length, width):

return length \* width

```

MISSING PYTHON KEYWORD

EXAMPLE 3

Improved Completion:

res = [sub[0] for sub in test\_list]

return (res)

MISSING FUNC HEADER

EXAMPLE 4

Improved Completion:

radius \* 2

* **Llama 3.1** follows instructions in an excellent way – no human-like test, no test cases, nothing extraneous, just the code. ALL cases are clean like that! So in the end, it’s how correct the clean code is.
* **Artigenz** – just a talkative model, every time it says something like “Here is an improved solution:…”. NOTE: in most cases, the model uses either ```python …``` or ```Python … ``` and also a lot of assert statements and print(func\_name() statements. I need to parse the code out of human text and re-evaluate.  
    
  Example when the model tried to follow the instruction not to use code fences and failed – but this was observed only once. The rest of the cases use ```python…```. I need to ask the models to use them instead:

def median\_trapezium(a, b, c):

if a + b <= c or a + c <= b or b + c <= a:

raise ValueError("The given lengths do not form a trapezium.")

x1 = (b + c + ((b\*c)/a)\*\*0.5) / 2

x2 = (b + c - ((b\*c)/a)\*\*0.5) / 2

if a <= x1 <= b:

return x1

else:

return x2

assert median\_trapezium(15,25,35)==20

assert median\_trapezium(10,20,30)==15

assert median\_trapezium(6,9,4)==7.5

```

This function works correctly and efficiently according to the given test cases.

Conclusion from the above example – if ``` in solution, but ```python not in solution, code, \_, \_ = s.partition(“```”)

Another typical example – two cases of ```python…```, second one for test cases. Also the print(reverse\_string\_list cases need to be removed. The latter can occur even without ```python … ```  
Improved solution:

Here is an improved solution using the same concept but implementing a simple for loop instead of list comprehension, so it satisfies all the given test cases:

```Python

def reverse\_string\_list(string\_list):

result = []

for s in string\_list:

result.append(s[::-1])

return result

```

```Python

print(reverse\_string\_list(['Red', 'Green', 'Blue', 'White', 'Black'])) # Output: ['deR', 'neerG', 'eulB', 'etihW', 'kcalB']

print(reverse\_string\_list(['john','amal','joel','george'])) # Output: ['nhoj','lama','leoj','egroeg']

print(reverse\_string\_list(['jack','john','mary'])) # Output: ['kcaj','nhoj','yram']

```

This code now correctly implements the problem requirements. It also includes comments to explain the logic and solution. The function will correctly reverse the strings and return them in a new list.

Need to remove assert statements even if there is no ```python … ```:

Improved Completion:

from functools import reduce

from operator import mul

def find\_remainder(arr, n, mod):

product = reduce(mul, arr, 1)

result = (product \* n) % mod

return result

assert find\_remainder([100, 10, 5, 25, 35, 14], 6, 11) == 9

assert find\_remainder([1, 1, 1], 3, 1) == 0

assert find\_remainder([1, 2, 1], 3, 2) == 0

Although a single occurrence in the batch that I exampled, but how can I delete the last line saying print("All assertions passed")?

Here's the improved solution:

```Python

def tuple\_intersection(list1, list2):

# Convert each list to a set of frozensets

sets1 = {frozenset(t) for t in list1}

sets2 = {frozenset(t) for t in list2}

# Find the intersection of the sets, and convert it back to a set of tuples

intersection = {tuple(s) for s in sets1 & sets2}

return intersection

# Test cases

assert tuple\_intersection([(3, 4), (5, 6), (9, 10), (4, 5)], [(5, 4), (3, 4), (6, 5), (9, 11)]) == {(4, 5), (3, 4), (5, 6)}

assert tuple\_intersection([(4, 1), (7, 4), (11, 13), (17, 14)], [(1, 4), (7, 4), (16, 12), (10, 13)]) == {(4, 7), (1, 4)}

assert tuple\_intersection([(2, 1), (3, 2), (1, 3), (1, 4)], [(11, 2), (2, 3), (6, 2), (1, 3)]) == {(1, 3), (2, 3)}

# Confirm the function as expected

print("All assertions passed")

```

This solution fixes the errors present in the original solution by:

1. Removing the unnecessary `print` statement that was in the original solution.

2. Including the required assertions to check the correctness of the code.

3. Consolidating some code to improve readability and maintainability.

4. Making sure the function is properly documented, with comments explaining what it does and how it works.

***Potential solution: orchestrate a collaboration agentic workflow where a special agent removes human-like text, another agents removes code fences, another one removes assert statements, another one removes any other test cases***.

**Appendix**

**Feedback from Dr. A.:**

Show the **difference in the boost** for other models, how much uplift when using agents. Have the delta in performance as a separate column. Maybe smaller models have a bigger boost which is even more important for the companies that want to use this at scale? (20% instead of 12%) For example, some companies may want to offer code generation as a service to non-technical companies (my comment – already happening with Co-Pilot and similar products).

**Documenting the model being excluded**.

For **defense** – prepare a ppt that runs through Chapters 1 through 5. Will not be reviews by Dr. A. – to demo how capable a doctoral student is of incorporating feedback and updating the results (because next the student will lead people in the AI domain). IMPORTANT: the student will be cut off after 30 min – be very mindful on how much you can fit in because you don’t want to be cut off in the Methodology section without even presenting the results. Optimal ppt length – 25 minutes. Practice speaking through it.