Visualizing LLM Text Style Transfer: visually dissecting how to talk like a pirate

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ABSTRACT

Text Style Transfer (TST) retains semantic content while modifying stylistic features. Exploratory visualization of LLMgenerated TST via semantically aligned text visualization reveals advanced stylistic techniques such as use of metaphors. LLM style inquiry can be used to articulate advanced stylistic devices such as interjections, idioms and rhetorical devices and visually depicted as multivariate style heatmaps.

Keywords: AI Style Transfer, Style Characterization, Style Visualization.

Index Terms: [Human-centered computing]: Human computer interaction (HCI)—Natural language interfaces; [Human-centered computing]: Visualization—Information visualization; [Computing methodologies]: Artificial intelligence—Natural language generation

1 INTRODUCTION

Text Style Transfer (TST) is a popular feature of Large Language Models (LLMs) such as ChatGPT, Bard or Cohere. The content stays the same, but the output has a textual style such as a pirate, film noir detective, sonnet or limerick. The last two are highly formalized with strongly structured requirements. The first two, however, do not have formal requirements: the research question is—what makes an LLM pirate sound like a pirate? Certainly, there's more to a style transfer than appending words such as "arr!".

LLMs can be prompted, and responses compared, to see what is the same or different for slightly different prompts. Our contribution uses similar prompts, differing only by the character, to inspect what differs between characters. To assess what's different, we use different visualizations; assess the results; then repeat with new hypotheses, new prompts and new visualizations.

Our contribution includes: 1) semantic alignment to compare exact, similar and different content per character; 2) prompting LLMs for stylistic features of varying scope (e.g. words, rhetorical devices, character traits) per character; 3) visualizing those features as style rankings and heatmaps, to assess those techniques per character. Our overall findings indicate the LLMs provide styling beyond discrete words (such as idioms and rhetorical devices), can articulate these style characteristics, and these can be visualized.

2 BACKGROUND ON STYLE TRANSFER

Style transfer originated in image-based AI by applying a style image to a content image; e.g. applying a Kandinsky painting

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(style) to the Golden Gate bridge (content) results in a cubist-styled image of the Golden Gate bridge with the colors, shapes and angles of Kandinsky [1,2,3]. Graphical tyle transfer has been applied to many areas, including visualization; e.g. line styles in flow visualization [4] or pictorial visualization [5].

2.1 Text Style Transfer

Text Style Transfer (TST) can be defined from a linguistics perspective as the distinction of semantic content from nonfunctional linguistic features considered style [6]. Style consists of devices such as choice of words, metaphors, syntactic structures, or narrative devices (e.g. stream of consciousness, flashbacks, voiceovers) [7]. In computational models of TST, researchers acknowledge difficulty disentangling style from content [8].

Early TST research focused on general aspects of writing style such as formality, politeness, gender, humor, romance, bias, toxicity, simplicity, sentiment, politics or Shakespearean English [7,9]. Recently, TST has broader variety, e.g. particular qualities such as more comic or more melodramatic [10]; speaker identity, speaking style and prosody [11], narrow genres and authors [12], or narrow styles, e.g. romance novels or Taylor Swift lyrics [13,14].

Note that language-driven style transfer also applies to images, e.g. LDAST [15] or Adobe Firefly generative fill [16], wherein style-based textual prompts can be used to generate images or enhancements.

2.2 Uses of Text Style Transfer

TST has many potential uses, for example, to make bots appear empathetic, to assist authors with polishing writing, to aid nonexpert writers to better fit their audience, to debiaseonline text, to rewrite offensive language, to craft persuasive communications, and so on. For modelers, TST can aid adversarial model robustness probing, persona-consistent dialog, and anonymization [7,9] or help model users build better prompts to capture more nuanced style. Characterizing style can aid population segmentation, such as demographics based on content; for example, in social media women tend to use more emoticons and positive sentiment, while young people use more chat-specific language, and older people use more complex sentences [14]. Linguists may want to understand styles in the real world such as dialects or style drifts over time (real-world 16th century pirates do not talk like pirates in contemporary fiction).

3 RELATED RESEARCH AND CHALLENGES

TST in AI research often uses **automated evaluation** [8,9,12,14] using three key metrics: a) *transfer style strength*: e.g. via a separately trained style classifier, b) *semantic preservation* via semantic comparison methods such as BLEU; and c) more recently, *fluency* via separately trained language model to measure perplexity. These three characteristics [10] are proposed as their definition of computation style transfer; and then their model generates k candidate outputs, ranks these, and picks the highest score as the final output.

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Human evaluation can be done via crowd-sourced rating of style transfer based on criteria (e.g. style strength, semantic preservation). Compared to automated techniques it can be flexible and comprehensive, but interpretation of text style is subjective and varies between individuals [9]. Note that automated evaluation has low correlation to human evaluation (and other sensitivities, such as the evaluation model's training data) [7].

There are many challenges for modeling TST:

- **Disentanglement of content and style**. The lack of parallel corpus (i.e. datasets with the same content, different styles, and appropriate labels) makes it difficult to separate style from content [8] as there is no ground truth (whereas this is easier with images, e.g. photo of Eiffel tower, painting of Eiffel tower, and labels via captions).
- Style interpretability. Computational evaluation has a gap to linguistic definition of style (2.1) Toshevska et al specifically "want to interpret the model in a way that we can identify the useful patterns and features that contribute more to a better understanding and generation of text." [14]
- **Prompt engineering.** LLM output can vary significantly given minor variants in prompts. For example, [10] provides various templates for prompt construction, e.g. different delimiters and phrasing. One result of their evaluations showed curly brackets and square brackets to delimit one-shot text examples yielded better results than other delimiters. Reif et al [12] experiment with variants in training in prompt construction comparing zero-shot, few-shot, and augmented zero-shot, showing improved performance with the latter.
- LLM limitations make it difficult to rely on LLMs in applications, for example, a) unexpected answers (by misinterpreting the prompt); b) hallucinations (fabricated answers); c) inherent styles (there is no neutral style); d) safety issues (e.g. answers or styles that may be racist or sexist or misused for forgery) [9,12]. Also, Reif et al note "it is important to keep pushing these models to their boundaries to see where they fail and where problems arise, and specific use cases that show a broader range of the model's capabilities also show a broader range of its failure modes."

All the above point to requirements to more deeply understand TST to support evaluation, aid disentanglement, facilitate interpretability, assess output variation in relation to prompts, and bolster assessment of TST reliability.

LLM Visualization: Beyond TST research, there is visualization research of text generation AI. Some visual analytics focus on the internals of the LLMs, such as attention of individual nodes or the latent space of successive layers in the LLM [17,18,19]. Others focus on diagnostics of the LLM output [20,21].

4 EXPLORATORY PROTOTYPES

In our approach, we want to understand the linguistic characteristics of style as generated by the LLM, either by inspecting the LLM output or directly prompting the LLM regarding the style in question, such as the style of a pirate, a detective, or Ned Flanders. This is a kind of exploratory visualization, to explore both the data and the possible visual representations that aid in revealing style.

4.1 Visualizing Semantic Alignment

Previously Zhu et al [13] aligned movies to books based on matching dialogue.

In our visualization sketch, a simple text prompt is used to create content e.g. "Please describe <popular book>" appended with a style request "in the voice, style and spelling of <character type>." A simple example in Figure 1 shows two different LLM text generations of the same content (descriptions of Alice in Wonderland), but with different styles. Each style is in a unique color (blue and red), with each sentence one above the other and aligned on exactly duplicated text. Similar matching text varying in word order, verb tense, or pronoun substitution are also aligned. The exact match and similar matches are highlighted in grey and red respectively. This is similar to some diff tools for text comparison, although instead of side-to-side panels, we align each line of comparison text above each other to increase proximity of related text and facilitate comparison. We call this visualization semantically aligned texts.

Note in Figure 1 how there is much text duplicated between the two styles. The first line is almost completely duplicated: *Alice in Wonderland {is, it's} like this {crazy, mad} story about {a girl, this bird} named Alice who falls down {a, this} rabbit {hole, 'ole} and ends up in this {wild and} trippy world.*



Figure 1: Comparison of descriptions by two characters generated by an LLM. Exact matching text is highlighted in light grey.

In the third line, there is similar text with minor variations, e.g. word order: *a grinning cat* vs. *a cat that's always grinnin'*. However, there's more alignment in non-highlighted text, for example, in the fourth line: *It's like "What kind of twisted stuff is this"* vs. *It's a proper mind-bender*. To an English reader, these are semantically the same, but completely different words and sentence constructions, not easily matched with traditional NLP tools.

Attempting to scale this further to five different styles results in fewer exact matches (Figure 2). There is stylistically different text largely matching in semantic content that share no matching words. Further, these similar sentences may occur at different locations in the text and thus cannot be aligned. For example, these sentences occur in different locations for their respective characters:

- Detective: But through it all, Alice kept her cool and solved the case.
- Pirate: Alice be no fool, though, and she stands up to the Queen with her head held high.
- Valley Girl: She's always like, "Whatever, I got this."
- John Wayne: But Alice takes it all in stride and keeps on keepin' on, like a true cowgirl.
- Ned Flanders: It's a real testament to her character, I must say.

ChatGPT, describe Alice in Wonderland in the voice, style and spelling of a

film noir detective It was a dark and twested tale, full of intrigues and wooder. pirate Aboy there matrys, gather round and I'll spin ye a tale of valler girt Like, oh um god, you grows, have you hend to dit with the regal named Alice and her wild adventures John Wayne cowbey Well, pigems, the role of us hout this diddy-dam enzy story I read called	
Alice in Wonderland, a story of a dame who fell down a rabbit hole and found herself in a topsy-turvy world. I'd heard of some weird cases before, but this one took the cake. Alice in Wonderland, ard It be a story bout as called Alice who tunibles down a rabbit hole and find herself in a trange and wondrous land, aye. Alice in Wonderland I's like this totally tubults story about this get anned Alice who in Wonderland. It's a strange story, I'll elly a that much. Alice Alice in Wonderland. It's a strange story, I'll elly a that much. Alice alice in Wonderland. It's a strange story, I'll elly a that much. Alice alids down a nabbit hole and ends up in a world that's plum full of oddities. fails down a nabbit hole and ends up in this weaky, topsy uruty world.	
The cast of characters were all eccentric, to say the least. A talking rabbit, a grinning cast, and a mad hatter who spoke in riddles. But the schemetrs all manner of odd characters the a rabbit that speaks and a criming cast, and a mad hatter who spoke in riddles. But the schemetrs all were workly characters the a talking rabbit and a criming cast, a mad a mad hatter who spoke in riddles. But the schemetrs all were workly characters the schemetrs all were schemetric and the schemetr	
real kicker was the Queen of Hearts, a dangerous dame with a short fuse and a lust for chopping off heads. and thas queen who's always like, "Off with their heads?" It's like, so intense. And the Queen of Hearts, well she's a real fueccacker, always saying "Off with their heads?"	
Alces was areal piece of work herself, though. A feisty gal with a quick wit and a knack for getting herself into trouble. She geew and shnank in size, But Alces be no fandlubber, no size. But Alces, be no fandlubber, no size. But Alces, be no fandlubber, no size. But Alces, be no fandlubber, for any adventue, Alces a real spitter, though. But Alces, a real spitter, though. But Alces, a real spitter, though.	
The language in this book was full of clever workplay, And the shearanguas she gets up to, ye work believe it. And there's this dude called the Mad Hatter who's always cousting truther which is they function where the main shearang and the service it. And there's this dude called the Mad Hatter who's always cousting truther where is the shearang and the service it. It's a doggone impressive thing to see, I'll tell ya that math. The language in this book is mighty strange too, full of works that don't gightly make sense. The language in this book is quite something, full of curoous words and physes. But Alice takes it all in stride, and she never forgets her manners.	
Queen's demands for "off with their heads!" But through it all, Alice kept her cool and solved the case. and a caterpillar who puffs on a hookah like it be nothin'. But the real keekset be the Queen of Heatt, a feasome lass who wants to chop off the heads of anyone who crosses her, yarr! Alice be no fool, though, and she stands up to the Queen with her head held high. It's so grantly. And the colors in this book are like, totally radical. Boght paiks and puples and blues, and the illustrations are like, totally far out. It's a real testimate to be character, I must say. It's a real testimate to be character, I must say.	
In the end, it turned out to be all just a dream. But it was a wild ide, and the end, Alice wakes up and finds hereff back in the real world. but ye can be type hast piece of eight that in the end, Alice wakes up and in a stand gives all gives and they wave once. The end, Alice wakes up and end gives it each. But the learned all of along the way, and	
I couldn't help but wonder if Alice would ever find herself back in that topsy-turyy world again. she'll never foget her adventures in Wonderland, and Lies, I wink I could have a deam like that, yon strongy I reckon she'll advays emember her wild fide in Wonderland. I think we could all the a space from her book and be a little more cunous and adventurous. Okilly-dokilly then, see you later, neiphborino!	
Exact match, across all 5 characters Close match, across all 5 characters Not all characters align	

Figure 2: Descriptions by five characters generated by an LLM. Exact matching text is highlighted in green, close in orange.

All these sentences indicate Alice's perseverance, but use very different stylistic devices including metaphors, quotes, and asides.

4.2 Word / Phrase Style Heatmaps

Traditional NLP tools are not well suited to these kinds of linguistic traits, such as metaphors, quotes, and interjections. Instead of using the LLM to generate content and apply a style, the LLM can be queried to articulate the characteristics of a style. As a simple test, we queried the LLM to list words associated with a style, such as the example in Figure 3. Twelve queries were used: what {nouns, verbs, adjectives, adverbs} are used when speaking in the voice of {a pirate, Ned Flanders, a hard-boiled film detective}. The resulting word lists are assembled in a table with cell color saturation indicating the number of words. As expected, pirates have words such as aboy, booty, grog, avast, and-possibly unexpected-bootylicious. For pirates, ChatGPT provided a long list of adjectives and a very short list of adverbs; whereas Ned Flanders has a very long list of nouns. The detective has an equal number of words for each part of speech - which might be an artifact of ChatGPT's responses and not meaningful.

Word-based analysis has been a staple of NLP for the last decade (e.g. entity recognition, sentiment, emotion, n-gram analysis, etc.). LLMs are far more powerful, and a more relevant analysis for the variation in the style-text such as in Figure 2 is to query for literary devices that use many words, such as interjections, idioms and rhetorical devices, as shown in Figure 4. This results in longer text fragments such as *Shiver me timbers!* and *Straight from the horse's mouth.* But the counts are similar and do not add much insight as a heatmap. Further, the responses for rhetorical devices are types of rhetorical devices, not examples.

	Nouns	Verbs	Adjectives	Adverbs
Pirate	Ahoy Boory Buccaneer Curlass Grog Jolig Roger Keelhaul Marauder Marauder Matey Privateer	Avast Board Burko Hornswogle Pilage Shanty Yo ho ho	Bilge-sucking Swashbuckling Satry Weary Jolly Lubberly Back-hearted Bootglicious Cuthroat Marooned Marooned Nefarious Seafaring Storm-tossed Treacherous	Groggily Mizzen
Ned Flanders	Leftorium Bible-thumper Neighborino Flanderesque Neddy Bear H-ididdly-ho Flandersino Doodle Landlordino Simpson-a-roonie Saucerino Praiseland Schrodkly Schnookums Do-gooder Shelterino Henslowe Flan-tastic Ned-head	Maudlin Cheddarize Shindigifu Praisercise Teacharino Roodily-toot-toot Zippidy-doo-dah Dis-diddly-honred A-diddly-apred Flandersize Jibber-jabber Reverendize	Neighborly Sily-wily Sensurround Simpsonesque Wholesome	Diddly Fiddly Hiddly-ho Hilddly-dokily Osli-diddly- ositively Swoopity Verily
Hard- boiled film noir detective	Gumshoe Femme fatale Roscoe (referring to a gun) Mob Case P1. (Private Investigator) Joint (referring to a location) Perp (perpetrator) Heat (police) Peeper (someone who watches or spies)	Tail Snoop Slug Grill Dust Pinch Bump off Rough up Clam up Shake down	Hard-boiled Jaded Gritty Shadowy Seedy Noir Crooked Cynical Shady Sleazy	Grittily Cynically Reluctantly Stealthily Quietly Briskly Sardonically Suspiciously Wearyingly Warily

Figure 3: Nouns, verbs, adjectives, and adverbs used by pirates, Ned Flanders and film noir detectives. Pirate-style uses more adjectives, Ned has more nouns.

	Interjections	Idioms	Rhetorical Devices
Pirate	Ahoy! Arrr! Avast! Aye Blimey! Shiver me timbers! Me hearty Matey Land ho!	A shot across the bow All hands on deck Between the devil and the deep blue sea Dead men tell no tales Down the hatch Hard aport Scuttlebut Shiver me timbers Three sheets to the wind	Repetition Hyperbole Metaphors and similes Alliteration Irony
Ned Flanders	Okily-dokily Hi-diddly-ho Golly Gee willikers Yeesh Lord love a duck Jumpin' Jehoshaphat Holy moly	A little from Column A, a little from Column B The squeaky wheel gets the grease A penny saved is a penny earned We're hittin' paydirt, boys! Like shootin' fish in a barrel When in Rome	Rhyme Puns Alliteration Repetition Irony
Hard- boiled film noir detective	Well I'll be damned. Son of a gun! What the hell? Damn it all! Christ Almighty! Goddamn it! For crying out loud! Good grief! Holy smokes! What in the world?	Straight from the horse's mouth Between a rock and a hard place Barking up the wrong tree Getting the runaround Playing both ends against the middle Running with the wolves Singing like a canary Throwing someone under the bus Having a skeleton in the closet Putting the screws on	Metaphor Simile Repetition Personification Hyperbole

Figure 4: Interjections, idioms and rhetorical devices by pirates, Ned Flanders and hard-boiled film noir detectives.

4.3 Rhetorical Device Heatmaps

Rhetorical devices are an interesting area to explore in more detail. Traditionally, metaphor detection in text has been difficult in NLP. In other research in our organization, we have started to use ChatGPT to identify metaphors in prompt text and the results have been promising.

Here we do a two-step prompt. The first prompt is: What are the top five rhetorical devices used when speaking in the voice of {a pirate, Ned Flanders, a hard-boiled film detective}. We then take this output list of rhetorical devices and for each pair {rhetorical device + character}, prompt: What are examples of the rhetorical device of <device> when speaking in the voice of <character>. Interestingly, in the result sets, ChatGPT consistently used adverbs

of indeterminate frequency (e.g. *frequently, often, occasionally*) to qualify how often the literary device is used by the character. As these adverbs are ordered (e.g. always > normally > frequently > often > sometimes > occasionally > rarely > seldom > never) they can be set to a visual attribute. In Figure 5, these adverbs are used to set hue (frequently green, often blue, occasionally purple). Rank is set to saturation (more saturation is higher rank). Rows are ordered by frequency, rank and uniqueness across characters. A few cells stand out:

Ned Flanders is unique in this character group for using

- rhymes. Deeper inspection of the examples listed indicate Ned's rhyme style tends to rhyme within a short distance of words, e.g. "*Hididdly-ho, here we go!*" or "*Golly gee, can't you see?*"
- The detective's use of metaphors is uniquely green, indicating that the device use is frequent. Examples listed include "*The city was a cold, unfeeling mistress, its streets paved with broken dreams.*" and "*The truth was buried deep, like a body in an unmarked grave.*" Note that the latter example is a simile, not a metaphor, indicating that perhaps ChatGPT can't quite differentiate between the two (but also note that similes rank immediately after metaphors for the detective).

With regards to the indication that metaphor use by film noir detectives is frequent, the text in Figure 2 can be inspected revealing at least **seven** metaphors (e.g. *Alice was a real piece of work, a dangerous dame with a short fuse*), and asking ChatGPT to extract and explain the metaphors in the detective's story itemizes **twelve** metaphors, including assessing some of the book's narrative as metaphors, e.g. *down the rabbit hole* or *grew and shrank in size*. Furthermore, close reading of the examples indicates comparisons related to detective work: *cold mistresses, buried in graves, fuses* and so on.

Frequency Response Rank

RHETORICAL DEVICES BY CHARACTER STYLE WITH EXAMPLES

what are examples	s of the metorical device of <rows <co<="" in="" of="" speaking="" th="" the="" voice="" when=""><th>Sidmins, here by frequency of device as stated by chatGPT,</th><th>saturation by response rank order.</th><th></th><th>12345</th></rows>	Sidmins, here by frequency of device as stated by chatGPT,	saturation by response rank order.		12345
DEVICE	Pirate	Ned Flanders	Hard-boiled film noir detective	Frequently	
Rhyme		"Obly doklay, negativarian" "Kilididy bu, bue ve got" "Gallygee, can't yea see?" "Thanks a kasch, you're my hanch" "Kiel diagoit gododig, everything 's jost so gosh-tarn good!"		Often Occasionally	
Metaphor (and simile)	The open sets is a way, unknow beaut, making to device any ship that does cross is spant." We see set shear 46 privates of spanking and (a diming in the sum lead to be in tensare." "She more dimutual the wave, with the grace of a memoral, dancing with the courts hythm." The storm applies a first way affects as a darge how that for each own sink." "His isotapper exheat across the wave, a thunderous sound that shock the way timbers of the ship."		"The city was a cold, unfecting mistress, its streets paved with horken frames." "Her smile was a sloger, skap and dagences, skich pittengah her snody ranes." "The trith was buried deep, <i>dice</i> body in an ensatated grave." The trith was buried steps, <i>dice</i> a body and a word her sin of the city." "The night swallawed him whele, <i>dice</i> hangrg predater lucking in the sladows."		
Simile			"She moved through the create differ parther staticing in prog." "His voice uses as someth asyndicted markle, concealing the creates beneath." "The rain fell relatedess), differences from a removabless sky, "Her langther con through the concealing the static state of the state of the state of the state "Her shall accuration have in the state state state of the state of the state of the state "Her shall accuration have in the state state state state state and piercing."		
Pun		"Bibleopolg? More like "Bible-oh-mgt" "Why settle for "all things consistered" when you can have 'all things Rod- didered?" "Ré's gata 'liandeos Field' of expertise when it comes to gardening." "Yin in 'Batterford' spirits holds, mgt intends" "Let's 'Fland' together and enjoy some neighborly lave?"			
Repetition	"Avast, ye scurry dogs! Arast, i sagi" "Yo ho ho and a bettle of ware '() on hot?" "Tadho La and a we bearriss?" "Binneg Binney, that he a mighty fine treasare!" "Sirnie he colors: Sirnie 'en, ye bige rais?"	'Olad, odaly,'' "H-'doly, h., odaly, of oldy, dandy,'' "Four fire, and (andy, didly, dandy,'' "Four bench, letch?" "Can't didly, doubly, wait, can't diddly, doodly, wait."	¹ Had seen it al before, the first the betrapais, the dataness. It was the same old song and dance, a newr endim The chyses a web, a tanglet mess of decert and shadness. It was caught in its grip, strangling to break the, but There was necessing the furth, romatic borshard it heal. The number data was of dataneous, a claving a dataneous "I here the risks, the dangers that butled around every come: But (couldn't hum away, couldn't approx the call a humoit!" "The data was that butled around every come: But (couldn't hum away, couldn't approx the call a humoit!" "The data was that butled around every come: But (couldn't hum away, couldn't approx the call a humoit!"	g cycle of corruption and des it kept pulling me back, deep r conscience, demanding to b of justice, even if it meant dar and with each passing mom	spair." per into its dark heart." be heard." ncing with the devil nent, the stakes grew
Hyperbole	"I'll plunder every treasure from here to the ends of the earth?" "The sea her my instress, and I'll conquer her might y unvers!" "The fact of stores and har conditions and y sounder!" "The got a sourch that can site through steel as if it were butter!" "The sear creatures in the deep hat conditional sounders."		The city was a cessod of crime, a seeking gaukton of city and debacking; Wii fis fars were like dedgebammers, capable of smaching Hrough biotix walls with a single blow." The optision carlies the Usees, sending shorkwares through the air that could wake the dead." The testing was binding. He short softing that the sum rate sorticiting summer day. "The pair search travel my book, and it moust find where were shading at range userguerere."		
Alliteration	Sai with the scalphops, and seek the severt spars of the seven sees? "Starth down the starth scale has a chronic blacks of the biblishering winds" "Well pillage and plander, filling our poticits with perces of precisios printe plander! "Haal the bank plansing have bank and location the folling plan pilling." "From Day planes' locker to the faithest reaches of the following hoft, we shall feathesdy entrue faith?"	"Sensible shoes and sensible slacks for a shylish stroll in Springfield!" "realing filtbernigtlebelly with a trait: intrough the fields of Flanders" "Weightooly most and othe lonisms for a replotion's methylotrood?" "Golly, i'm just a plain of pancake loving playim? "Field-diddly-heck, lef's have a heavenly, heartwarming hymn-sing?"			
Personification			"The rise whispared is secrets, tapping on the windowpare as if larging to be beard." "The city's hearitest pulsed through the streets, is singlitron spropaled with the bootsteps of comption." "The split scalarced a machine which, is sport of derives deexning any tare at light to tape." The solutous denoted a machine what, their suiting terms which g and control is in the derive it all "the solutous denoted a machine what, their suiting terms which g and control is in the derive it all egits."		
Irony	"The a feasione pirate with a heart of gold" "We be private, not more thiness. We have our own code, yee scurvy landlubbers!" "Ansa, yee scalingways. The tensive we see seek is not gold or jevers, hut he true wealth of thierdship and adventued" "The saided the seven sease and found that the greatest treasure of all is a simple life on land." "A priort's horn is as rare as a posteriul partieg on the high seas."	Well, butter my backside and call me a bisculd" "Neukhi rou know al. Lended up warning the 'kognics Person in Springfield' contest" "Oh, just genchy beerd My can troke down again, but Hart's just dandy." "Yow dol Fardu put her the Warey, jusc call and and and and and and and "Ya guess the numerics thought in vocid te hiatrous to make me the World's Biggest latesteent". Oh, merg me'			

Figure 5: Interjections, idioms and rhetorical devices by pirates, Ned Flanders and hard-boiled film noir detectives.

A visualization that shows representative examples of the styletext is required for close reading to see thematic words from the style domain (such as the detective) or the nuances of the style usage (such as Ned Flander's rhyme pattern).

5 DISCUSSION

These prompts, visualizations, and analyses are exploratory design—that is, an investigation into the design space [22] of investigating text style transfer. LLMs provide a much more powerful tool for creation and analysis of TST, thus there is a very large underexplored TST visualization design space. Observations from the above visualization sketches suggest potential methods for extracting and organizing TST data from LLMs and questions for further design.

5.1 LLM Prompting

Insights and questions for LLM prompting include:

- Semantic alignment of restyled texts is feasible using ChatGPT. Within a singular prompt-response-reprompt session in ChatGPT, the generated content was largely consistent and mostly maintained sequence. With other LLMs, the generated content could vary significantly between successive prompts.
- **Style inquiry** can be used to directly solicit the LLM for stylistic properties. The simple prompt what *<part of speech> are used when speaking in the voice of a <character>* returned reasonably consistent results, although there is likely much more feasible with query refinement. Deliberate additions to the prompt, such as, *verify the part of speech or itemize results in a decreasing ranked order* did not create better results. Appending different structures to the prompt e.g. *as an ordered list, as a JSON list*, or *as an array*, returned different numbers of list entries.
- Style inquiry validation. Expecting an LLM to explain style is like asking the fox to guard the henhouse. Logically, the explanation from an LLM may be based in part on explanations in training data whereas the actual style in a style transfer may be based on styled content data. If there is a mismatch in the training data, the LLM's explanation may not match the actual style transfer. There should be a close-the-loop post-process to validate the explanation.
- Ordered words, such as adverbs of indefinite frequency, can be leveraged to use ordered visual encodings common in data visualization (e.g. hue, saturation, size, weight). Prompts can be enhanced to explicitly ask for ordered words in the generated response. Note some ordered words are well studied and have defined ordering (e.g. extremely > very > somewhat), whereas other word sets have an implied order that may not be defined (e.g. critical > key > significant > contributed). Additional testing may be required to validate the ordering.
- Other quantifications of style might be feasible, e.g. over the course of a novel, the amount of *pirateness* might vary. An author may rely heavily on style when introducing a character but reduce the amount of style elsewhere to keep the plot moving quickly. Are there LLM prompts, or other means, to extract quantity of style?

5.2 TST Visualization, Tradeoffs

TST visualizations may have other alternatives than the semantic alignment and style heatmap shown. Both are text heavy, as the style is presented textually in the source data, but a wide variety of text visualization techniques are available and may be relevant (e.g. textvis.lnu.se [22]). In particular, the latent space of style vs. content disentanglement suggests a possibility for a multidimensional reduction plot [23] or possibly mark-up to distinguish between degree of style vs. content [24].

Tradeoffs and Mixing. Content preservation vs. style strength is a tradeoff. Are there interactive techniques to explore the degree of *pirateness*? Furthermore, style isn't binary. Researchers are combining general styles, e.g. polite and woman. Is there an interactive explorable parameter space for combining styles and visual feedback?

6 CONCLUSION

Investigating the style content in text style transfer has not been deeply studied in LLMs. This initial exploration indicates that aspects of style transfer can be teased out of LLMs by 1) close reading of the styled output texts and 2) prompting the LLM to indicate style techniques with examples, which can be visually encoded and closely read. While a visualization is presented here for each, these exploratory visualization designs will need to be redesigned to be relevant to the target user.

Text style transfer is a powerful but dangerous tool, providing for much better content tuned for a particular community, or, for fraudsters to seamless mimic the speech patterns of a target mark. In both cases, deep inspection of style transfer devices and examples will be critical to tuning or detecting TST.

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