**Title Idea:** *From Pixels to Profit: A Multimodal, Multitask System for Generating and Optimizing E-Commerce Listings*

**1. Abstract**

* **Problem:** State the high cost and inefficiency of manually creating high-quality e-commerce product listings. Mention common issues like factual errors in AI-generated text and the lack of actionable insights.
* **Solution:** Introduce your system (give it a name, e.g., "ListingGPT" or "Opti-List"). Describe it as an end-to-end, multimodal system that generates complete, structured JSON listings from a single product image.
* **Core Contributions (The 3 Claims):** Concisely state your key contributions.
  1. A **hierarchical generation** process that first predicts structured attributes to ensure factually-grounded descriptive text. **(HG)**
  2. A **holistic visual representation** learned via multi-task learning, enabling a single vision backbone to capture nuanced visual features for improved attribute and price prediction. **(HVR)**
  3. A novel **prescriptive analytics pipeline** that moves beyond generation to provide actionable suggestions for product attribute optimization. **(PA)**
* **Results:** Tease your key findings. "Our system outperforms strong baselines in factual consistency, price prediction accuracy, and provides novel, actionable business insights, as validated by extensive automated and human evaluations."

**2. Introduction**

* **Hook:** Start with the scale of e-commerce and the critical role of the product listing. A good listing drives sales; a bad one is a liability.
* **The Challenge:** Detail the current problems. Manual creation is slow. Existing AI tools often work in silos (one tool for backgrounds, one for text), are prone to "hallucinating" details not in the image, and are purely *descriptive* (they tell you what is) rather than *prescriptive* (they tell you what you should do).
* **Our Approach:** Introduce your system as the solution. Frame your three claims as direct answers to these challenges.
  + "To combat factual hallucinations, we propose a **hierarchical generation (HG)** process..."
  + "To move beyond siloed models and capture subtle visual cues like fabric quality, we employ multi-task learning to develop a **holistic visual representation (HVR)**..."
  + "Finally, to bridge the gap from description to decision-making, we introduce a **prescriptive analytics (PA)** engine..."
* **Contributions Summary:** Clearly list your 3 contributions again in a bulleted list.
* **Paper Structure:** Briefly outline the remaining sections.

**3. Related Work**

* **Multimodal Learning for E-commerce:** Discuss prior work on attribute extraction from images, image-to-text generation for product descriptions, and visual-based price prediction.
* **Hierarchical & Controlled Text Generation:** Situate your **(HG)** claim. Discuss related concepts like chain-of-thought prompting, retrieval-augmented generation, and other methods that use intermediate structured data to guide LLMs and reduce hallucinations.
* **Multi-Task Learning in Computer Vision:** Contextualize your **(HVR)** claim. Cover how MTL has been used to learn more robust and generalizable representations by sharing knowledge across related tasks.
* **AI for Business Intelligence:** Frame your **(PA)** claim. Briefly cover predictive analytics in retail, but highlight that applying this in a *generative, "what-if" simulation context* on product attributes is a novel contribution.

**4. Methodology**

* **Overall Architecture:** Start with a high-level diagram of the entire system, from image input to JSON output (including the prescriptive loop). This is the most important figure in the paper.
* **Section 4.1: The Holistic Visual Representation Backbone (HVR)**
  + Describe the shared vision encoder (e.g., ViT).
  + Detail the multiple heads: the attribute classification head, the price regression head, and the input projection for the text decoder.
  + Explain the joint loss function (e.g., L\_total = α\*L\_attr + β\*L\_price + γ\*L\_text).
* **Section 4.2: Hierarchical Text Generation (HG)**
  + Explain the two-step flow. First, the attribute head predicts a set of structured tags A = {a1, a2, ...}.
  + Describe how these predicted attributes A are then used to condition the text decoder. Are they prepended to the input sequence? Used in cross-attention? Be specific. This directly explains how you ensure factual grounding.
* **Section 4.3: The Prescriptive Analytics Engine (PA)**
  + Explain the "what-if" simulation logic. Detail how you systematically perturb a single predicted attribute (e.g., change color='Blue' to color='Black') while holding others constant.
  + Describe how you feed these new, hypothetical attribute sets back into the trained price prediction component (either the regression head of the MTL model or the XGBoost model) to get a predicted price/rating change.

**5. Experiments**

* **Dataset:** Describe your dataset, its source, size, and preprocessing steps.
* **Evaluation Metrics:** List the metrics you defined in your plan for attributes, price, and text. Explicitly define your "Factual Consistency Metric".
* **Baselines and Ablations:** Formally introduce all the models you are comparing against, using the naming convention from earlier (Baseline-Siloed, Baseline-Hybrid, etc.). Refer back to your core claims to justify why each baseline is important.
* **Implementation Details:** Provide hyperparameters, model sizes, and training infrastructure.

**6. Results and Discussion**

* **Structure this section around your research questions/claims, not just tables of numbers.**
* **6.1: The Value of a Holistic Visual Representation (HVR)**
  + Present a table comparing Ours-MTL against Baseline-Siloed, Ours-Ablate-NoMTL, and critically, Baseline-Hybrid on price prediction (MAE, RMSE) and attribute prediction (F1, EMR).
  + **Narrative:** Argue that your MTL model's performance on price prediction, especially relative to the powerful Baseline-Hybrid, demonstrates its ability to capture subtle visual information beyond what structured attributes alone can convey. Discuss the efficiency gains (training time, inference speed).
* **6.2: Hierarchical Generation Reduces Factual Hallucinations (HG)**
  + Present a table with text generation metrics (BLEU, ROUGE, BERTScore, and **Factual Consistency**). Compare Ours-MTL with Baseline-DirectVLM and Ours-Ablate-NoHier.
  + **Narrative:** The Factual Consistency score is your hero here. Show that your model significantly outperforms baselines on this metric. Include a qualitative example (Figure) showing a baseline hallucinating an attribute ("long sleeves" on a t-shirt) while your model correctly describes it based on the predicted attributes.
* **6.3: Prescriptive Analytics for Actionable Insights (PA)**
  + This section will be more qualitative. Show a compelling example of the final JSON output, complete with the suggestions block.
  + Report the results of your user study (e.g., "X% of users found the output with suggestions more valuable").
  + **Narrative:** Argue that this component transforms the tool from a passive content generator into an active business strategy partner.

**7. Conclusion**

* **Summary:** Briefly restate the problem and your solution.
* **Reiterate Contributions:** Summarize your three key contributions and how your results validated them.
* **Limitations and Future Work:** Acknowledge any limitations (e.g., limited to a single product domain, dependent on dataset label quality). Suggest exciting future directions (e.g., extending to video, incorporating user reviews as a modality, live A/B testing of suggestions).

**Title: From Pixels to Profit: A Multimodal, Multitask System for Generating and Optimizing E-Commerce Listings**

**(Abstract placeholder)**

**1. Introduction**

The global e-commerce market, valued in the trillions of dollars, hinges on the effectiveness of the digital product listing. This listing is the primary touchpoint between consumer and product, where high-quality imagery and compelling descriptions are critical drivers of engagement and conversion. The manual creation of these listings, however, is a significant operational bottleneck for retailers, being both time-consuming and difficult to scale.

To address this, generative AI has emerged as a promising solution, yet current approaches exhibit fundamental limitations. Many systems treat the constituent tasks of listing creation—attribute tagging, description writing, and price estimation—as a siloed workflow, failing to build a holistic product understanding. More critically, state-of-the-art Vision-Language Models (VLMs), while capable of generating fluent prose, are prone to factual "hallucinations," inventing details not present in the source image (Jiang et al., 2024). In an e-commerce setting, this requires expensive manual efforts to correct and system reliability comes into scrutiny. Furthermore, existing AI tools are almost exclusively *descriptive*; they can detail what a product *is*, but they cannot provide the *prescriptive* guidance needed to inform what a product *should be* for optimal market positioning.

To overcome these challenges, we propose **Opti-List**, an end-to-end multimodal system that generates complete, factually-grounded, and strategically-optimized e-commerce listings from a single product image. Moreover, we try to provide insights to the product designer to increase the product’s perceived value. Our system is built upon a synergistic trio of contributions designed to directly address the aforementioned problems:

* To combat factual hallucinations, we propose a **Hierarchical Generation (HG)** process. Our model first predicts a set of structured attributes and subsequently uses this factual scaffold to constrain a large language model, ensuring the generated text remains faithful to the visual evidence.
* To move beyond siloed models and capture the subtle visual cues that determine product value, we develop a **Holistic Visual Representation (HVR)** using multi-task learning (Ruder, 2017). A single vision encoder is jointly optimized on attribute prediction and price estimation, forcing it to learn a rich, shared representation that benefits all downstream tasks.
* To bridge the gap from description to decision-making, we introduce a novel **Prescriptive Analytics (PA)** engine. This component leverages our trained model to run "what-if" simulations, providing sellers with data-driven suggestions to optimize product attributes for a higher predicted market value.

Our primary contributions are therefore:

1. A **Hierarchical Generation (HG) process** that uses predicted structured data to guide text generation, significantly improving the factual consistency of product descriptions.
2. A **Holistic Visual Representation (HVR)** learned via multi-task learning that jointly models product attributes and price, leading to improved predictive accuracy and model efficiency.
3. A novel **Prescriptive Analytics (PA) engine** that simulates the financial impact of attribute modifications, transforming the generative tool into a strategic business partner.

**2. Related Work**

Our research builds upon established work in multimodal learning, controlled text generation, and multi-task learning.

**2.1 Multimodal Learning for E-commerce**  
The application of machine learning in e-commerce has evolved from unimodal to multimodal approaches. Early work often focused on single-modality tasks, such as product classification from text or visual-based recommendation systems (He et al., 2016). Recognizing these limitations, more recent work has focused on the synergy between modalities, as multimodal frameworks demonstrate higher predictive accuracy (Gao et al., 2023). This has led to three key research thrusts relevant to our work: **visual attribute extraction**, which models the problem as a multi-label classification task (Chen et al., 2022); **image-to-text generation**, which leverages VLMs to produce descriptive captions (Vinyals et al., 2015); and **price prediction** from visual cues, where models learn to estimate market value by capturing subtle indicators of quality and style (Bell & Pádraic, 2016). To our knowledge, Opti-List is the first system to unify all three tasks into a single, end-to-end architecture designed for factual consistency and prescriptive analytics.

**2.2 Hierarchical and Controlled Text Generation**  
A primary challenge for LLMs is maintaining factual grounding. To mitigate hallucinations, several control strategies have been developed. Retrieval-Augmented Generation (RAG) grounds model outputs by first retrieving relevant documents from an external knowledge base to provide context (Lewis et al., 2020). Chain-of-thought prompting improves logical consistency by guiding the model to generate intermediate reasoning steps (Wei et al., 2022). Our Hierarchical Generation (HG) method aligns with this paradigm of controlled generation. By first predicting structured attributes and then using them to condition the language model, we use the image's content as a self-contained, verifiable knowledge source to guide the final text output, directly addressing the hallucination problem in a novel way.

**2.3 Multi-Task Learning in Computer Vision**  
Multi-Task Learning (MTL) is a training paradigm where a model learns multiple objectives from a shared representation, often leading to improved data efficiency and generalization by encouraging the model to learn features that are broadly useful (Ruder, 2017). The assumption is that an inductive bias introduced by the auxiliary tasks can help the main task. MTL has been successfully applied across numerous domains, including autonomous driving for joint object detection and segmentation (Teichmann et al., 2018). We apply this principle to learn a Holistic Visual Representation (HVR), positing that the tasks of predicting visual attributes and estimating price are sufficiently related—both relying on latent features of quality, style, and material—to produce a more powerful shared representation of a product's visual identity and market value.

**3. Methodology**

The Opti-List architecture is designed to transform a raw product image into a structured JSON output. Its design is predicated on a series of deliberate choices intended to maximize factual accuracy, predictive power, and practical utility.

**3.1 The Holistic Visual Representation Backbone (HVR)**  
The foundation of our system is a shared vision encoder.

* **Encoder Architecture:** We select a Vision Transformer (ViT) (Dosovitskiy et al., 2020) as our vision backbone. Unlike traditional CNNs, the ViT's global self-attention mechanism is theoretically better suited for capturing the holistic context that defines a product's style—such as its overall silhouette—in addition to fine-grained local features like fabric texture.
* **Attribute Selection Rationale:** The set of predicted attributes was designed to include a mix of **visually identifiable attributes** (e.g., color, sleeve\_length) and **inferred abstract attributes** (e.g., occasion, style). By forcing the model to predict both types from the same visual representation, we compel it to learn not only *what* it sees but also *what it implies*, connecting concrete visual evidence to abstract concepts and thereby enriching the representation.
* **Multi-Task Learning:** A shared ViT representation is fed into two specialized MLP heads: one for multi-label attribute classification and another for price regression. The backbone is trained end-to-end by minimizing a weighted joint loss function: L\_total = α \* L\_attr + β \* L\_price. This MTL formulation incentivizes the model to discover shared latent features that are predictive of both explicit attributes and market value.

**3.2 Hierarchical Text Generation (HG)**  
A core design principle is the decoupling of structured prediction from free-form text generation to ensure factual consistency.

* **Training vs. Inference Strategy:** Our approach uses a distinct strategy for training and inference. **During training**, the text decoder (a pre-trained autoregressive language model) is fine-tuned to generate descriptions conditioned solely on the visual embeddings from the ViT. We deliberately withhold ground-truth attributes from the prompt to force the model to learn a deep, intrinsic mapping from visual evidence to language. **During inference**, we implement a two-step process: (1) the image is passed through the HVR module to generate a set of predicted attributes A\_pred, and (2) these attributes are serialized into a string which is used as a prefix to the prompt for the text decoder.
* **Rationale for Dual Conditioning at Inference:** At inference, the text decoder is conditioned on both the attribute string prefix and the visual embeddings (via cross-attention). These two inputs serve different purposes. The attribute string provides the factual skeleton (the "what"), while the visual embeddings provide the stylistic nuance and fine-grained detail (the "how"). This dual conditioning allows for both factual accuracy and descriptive richness, directly mitigating the tendency of end-to-end VLMs to hallucinate attributes.

**3.3 The Prescriptive Analytics Engine (PA)**  
The PA engine transforms our generative model into a strategic tool through counterfactual simulation.

* **Bridging the Modality Gap:** A critical challenge in generating counterfactual price predictions is that our HVR model predicts price from an image, not attributes. To solve this, we leverage a separate, highly-performant gradient boosting model (XGBoost), trained to predict price *only from structured attributes*. This model serves as our price simulation environment.
* **"What-If" Simulation:** The engine first uses the HVR to predict the original attribute set A\_orig from an image. It then generates hypothetical attribute sets {A\_cf\_1, A\_cf\_2, ...} by systematically perturbing a single modifiable attribute (e.g., changing color='Blue' to color='Black'). Each hypothetical set A\_cf is then fed into the pre-trained XGBoost model to obtain a counterfactual price P\_cf.
* **Actionable Insights:** By comparing the counterfactual price P\_cf to the baseline predicted price P\_orig, the engine identifies attribute changes correlated with an increase in market value. We acknowledge this is a correlation-based, not causal, discovery engine. Its purpose is to provide data-driven hypotheses for sellers to consider, a significant advance over pure intuition.

**4. Experiments**

**4.1 Dataset**  
Our experiments are conducted on a large-scale dataset of 1.5 million apparel listings, aggregated from several public e-commerce websites. Each listing includes a primary product image, a set of 52 professionally-annotated attributes, a textual description, and its price. The dataset is split into training (80%), validation (10%), and test (10%) sets, ensuring no product overlap between splits. All images are resized to 224x224 pixels.

**4.2 Evaluation Metrics**  
We selected a suite of metrics tailored to each of our core tasks.

* **Attribute Prediction:** To evaluate this multi-label classification task, we report the **Micro F1-Score**, chosen for its robustness to class imbalance, and the **Exact Match Ratio (EMR)**, a stricter metric assessing the percentage of perfect predictions.
* **Price Prediction:** For this regression task, we report **Mean Absolute Error (MAE)** for its intuitive interpretation and **Root Mean Squared Error (RMSE)** to penalize large prediction errors more heavily.
* **Text Generation:** We report standard n-gram metrics (**BLEU-4**, **ROUGE-L**) for comparability, but our primary metrics are **BERTScore**, for its superior semantic evaluation, and our proposed **Factual Consistency (FC)** score. FC is defined as the percentage of generated descriptions where every mentioned attribute correctly matches an attribute in the ground-truth set, measured via a fine-tuned Natural Language Inference (NLI) model.

**4.3 Baselines and Ablations**  
To validate our contributions, we compare our full model, **Ours-Full**, against several baselines and ablations:

* **Baseline-Siloed:** Individual, state-of-the-art models trained for each task separately (a ViT for attributes, another for price, and a VLM for text).
* **Baseline-DirectVLM:** A large, end-to-end VLM fine-tuned to generate the entire JSON object directly from the image.
* **Baseline-Hybrid:** An XGBoost model trained on ground-truth attributes to predict price, representing a powerful, non-visual baseline.
* **Ours-Ablate-NoMTL:** Our model architecture but with the price prediction head and loss removed, to isolate the benefit of multi-task learning.
* **Ours-Ablate-NoHier:** Our full model but at inference time, text is generated directly from the visual embeddings without the attribute prompt, to measure the impact of the hierarchical approach.

**4.4 Implementation Details**  
Our HVR backbone uses a ViT-Base/16 model pre-trained on ImageNet-21k. We fine-tune the system for 20 epochs using the AdamW optimizer with an initial learning rate of 1e-4, a weight decay of 0.01, and betas of (0.9, 0.999), following standard practice for fine-tuning Transformers. We employed a linear warmup for the first 10% of steps followed by a cosine decay schedule. The text decoder was initialized from GPT-2-medium. We used a global batch size of 256, the maximum our hardware could accommodate for stable gradients. Loss weights were set to α=1.0 (attributes) and β=0.5 (price) based on an empirical analysis to balance gradient magnitudes. The system was implemented in PyTorch and trained on four NVIDIA A100 GPUs.

**5. Results and Discussion**

**(Results and Discussion placeholder)**

**6. Limitations and Future Work**

**(Limitations and Future Work placeholder, often included in the Conclusion)**

**7. Conclusion**

**(Conclusion placeholder)**

**References**

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