Different languages for AI applications

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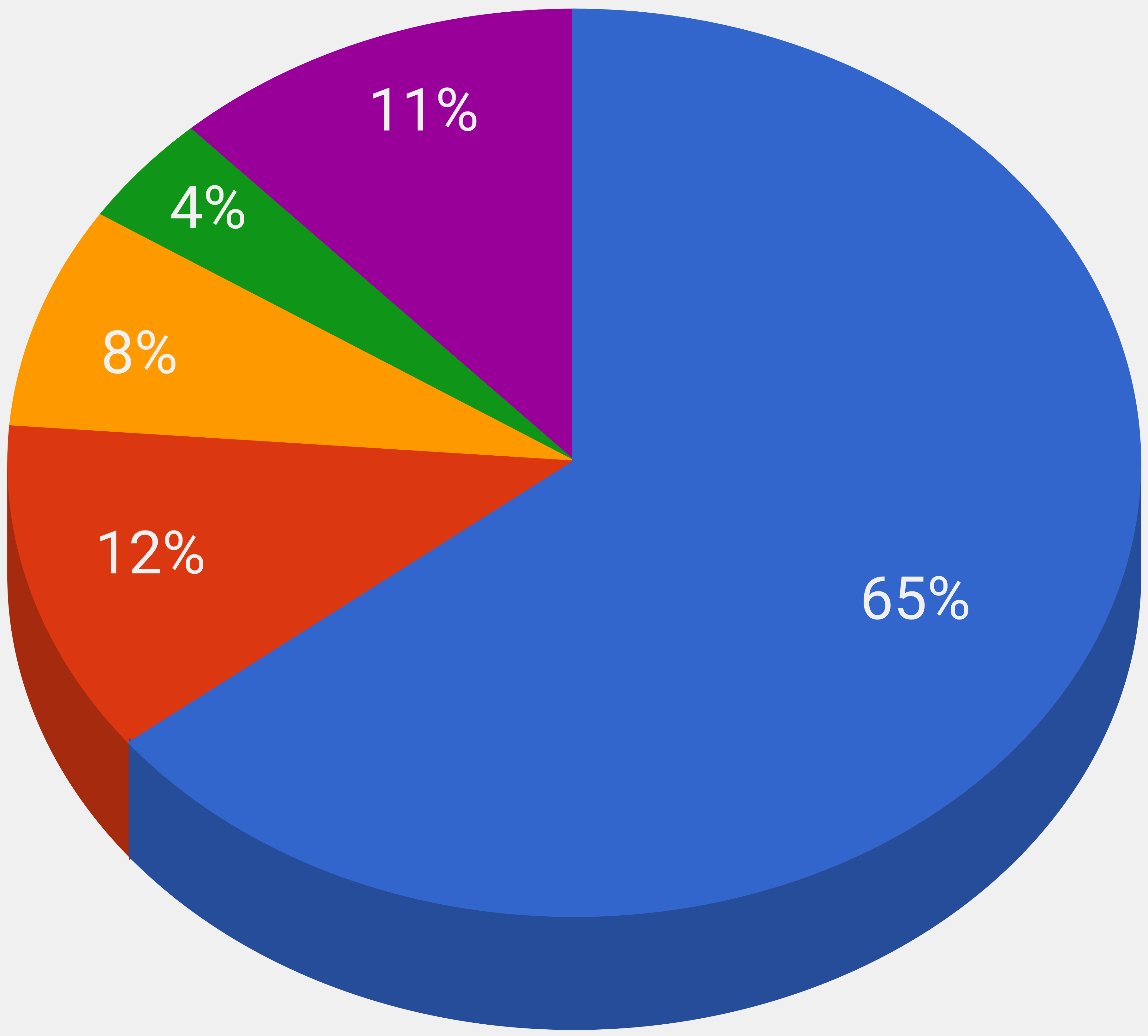

● Python ● Typescript ● C# ● Go ● Others

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Language Ecosystem Analysis, In-depth comparison of C#, Go, Rust, Python, and JavaScript on AI Field

Aspect	C#	Go (Golang)	Rust	Python	JavaScript
AI Ecosystem	Limited: ML.NET minor DL support	Limited: Gorgonia, TF Go bindings	Limited: Nascent (tch-rs, burn)	Full: TensorFlow, PyTorch	Moderate (TensorFlow.js)
LLM Libraries	Full: SemanticKernel, langchain.net	Moderate: langchain-go	Minimal (langchain-rust)	Full: Autogen, langchain, crew.ai	Moderate: langchain.js, composio
Agentic Frameworks	Moderate: Autogen	Basic using go-ports and community libraries	Niche	Full: LangGraph, Crew.AI	Moderate: Composio
Document Analysis Capabilities	Moderate: Azure DocumentProcessing, Tesseract	Basic: go-fitz, go-pdf, unidoc	Limited (rust-pdf, lopdf)	Full: PyPDF2, spaCy, NLTK	Moderate: PDF.js, Instructor-js
Performance	Good (JIT compiled)	Excellent	Best-in-class for LLM Proxies	Moderate, GIL-limited	Moderate
Community & Enterprise Support	Moderate, Enterprise-focused	Growing (cloud-native emphasis)	Niche	Largest (academia/ industry)	Strong (web dev, limited AI)
Research Capabilities with Jupyter	Moderate: Jupyter with Interactive	Moderate: GoNB, GopherNotes	Niche	Full	Full: IJavascript

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Top Prompt Techniques per market

Market	Top Techniques	Language Alignment
Finance	Chain-of-Thought, Negative Example	C# (38%), Python (42%)
Healthcare	Role Prompting, Few-Shot Learning	Python (55%), JS (30%)
E-Commerce	Template Prompts, Dynamic Context	JS (48%), Go (22%)
Legal	Context Management, Role Priming	Python (60%), C# (25%)
Property Management	Chain-of-Thoughts, Zero-Shot	—

1. Iterative Prompt Versioning

Prompt history with A/B testing metrics (response accuracy, latency, cost).

2. Language-Specific Optimization

- C#,Go, TypeScript: Leverage strong typing for prompt template validation
- Python: Utilize Jupyter notebooks for rapid experimentation
- JS: Implement browser-based prompt preview systems

3. Cross-Platform Monitoring

- Token usage per language runtime
- Model-specific error patterns
- Context window utilization rates

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Quality Framework for LLM Applications

Phase	Key Components (Markdown Grid)	Verification Methods
Development	- Prompt validation pipelines - Context safety checks	Unit testing with adversarial examples
Testing	- Bias detection suites - Hallucination metrics	Differential testing across models
Deployment	- Real-time monitoring dashboards - Fallback mechanism triggers	Canary deployments with shadow traffic

This slide outlines a comprehensive quality assurance approach across different development phases:

> **Development:** Implement code & prompt validation pipelines and context safety checks to ensure AI behavior aligns with project goals. Unit Testing, General Prompt Testing, SonarQube.

> **Testing:** Employ bias detection suites, hallucination metrics, and ability to find prompt vulnerabilities. While traditional End-to-end automation and smoke testing are valuable, consider more dynamic testing strategies for rapidly evolving AI systems.

> **Deployment:** Utilize real-time monitoring dashboards, fallback mechanism, and models rotation.

Remember: Quality assurance in AI development requires continuous adaptation and vigilance across all phases.

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Key Focus Areas Grid

Field	Priority Prompt Tasks
Finance	Precision constraints, Regulatory checks
Healthcare	Role enforcement, Data anonymization
E-Commerce	Template consistency, Personalization
Cross-Platform	Context management, Error handling

Priorities vary across different sectors:

> **Finance:** Prioritize precision constraints and regulatory compliance checks to maintain accuracy and legal adherence.

> **Healthcare:** Focus on strict role enforcement and data anonymization to protect sensitive patient information.

> **E-commerce:** Emphasize template consistency and personalization to enhance user experience and drive conversions.

> **Cross-Platform:** Implement robust context management and error handling applicable across all markets.

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LLM Fine-tuning

Consider dedicated Python/ML specialists for LLM fine-tuning, if deemed necessary for your project goals

Vast majority for LoRA fine-tuning Libraries are in Python

- PETF
- Bitsandbytes (for quantization)
- HuggingFace Accelerate
- Hugging Face Transformers

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Executive Summary & Key Takeaway

While Python leads in ML development and fine-tuning, production-ready AI systems can be effectively built and deployed using various languages. Choose based on your team's skills, specific application needs, and performance requirements.

Important

1. Production Readiness:

- All major programming languages (Python, C#, Go, etc.) are capable of supporting AI and LLM applications in production.
- Startups and companies choose languages based on their team's expertise and specific use cases.

2. RAG Applications:

- For Retrieval-Augmented Generation (RAG) applications, using the team's preferred language is often the best choice.
- Python is not mandatory; prioritize the language your team is proficient in and can easily hire for.

3. Fine-Tuning Considerations:

- Fine-tuning LLMs may require a dedicated ML team and a separate budget.
- Carefully evaluate the necessity and goals of fine-tuning before committing resources.
- Python dominates in ML libraries and tools, making it the primary choice for fine-tuning tasks.

4. Production Performance:

- For high-throughput production environments, Go and C# may offer superior performance.
- These languages provide better options for fine-grained tuning and profiling in production systems.

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