In [ ]:

```python
# Import statements
import subprocess
import os
import json

import pandas as pd
import statsmodels.api as sm

from IPython.display import display, Image, Markdown
```

In [2]:

```python
# Hardset vars
dataset_path = "data/processed/labeled_asset_dataset_enriched.csv"
config_path = "config/generation_params.json"
alt_config = "config/alt_scenario_generation_params.json"
```

In [3]:

```python
# Utility functions for running the MLflow pipeline, resetting it, and displaying r
def reset_pipeline():
    """Reset the pipeline by running the reset_pipeline.py script."""
    result = subprocess.run(
        ["python", "scripts/reset_pipeline.py"],
        capture_output=True,
        text=True,
        encoding="utf-8",
        errors="replace"  # prevent crashes from non-UTF-8 characters
    )

    print(result.stdout)
    if result.stderr:
        print(result.stderr)


def display_config(config_path):
    """Load and display the contents of a configuration file as formatted JSON."""
    if not os.path.exists(config_path):
        print(f"⚠️ Config file not found: {config_path}")
        return

    with open(config_path, "r") as f:
        params = json.load(f)

    display(Markdown(f"### Contents of `{config_path}`:"))
    display(Markdown(f"```json\n{json.dumps(params, indent=4)}\n```"))


def run_pipeline(dataset_path, alt_config=None, steps=None):
    """
    Run the MLflow pipeline fully or step-by-step.

    Args:
        dataset_path (str): Path to the dataset CSV.
        alt_config (str, optional): Alternate config file for the generate step.
        steps (list, optional): Specific pipeline steps to run.
                                If None, runs the full pipeline entry point.
    """
```

```
    # Determine processed_dir based on dataset_path
    processed_dir = os.path.dirname(dataset_path)

    # Ensure processed_dir exists
    os.makedirs(processed_dir, exist_ok=True)

    # If dataset exists and no steps were specified, just load the data
    if steps is None:
        try:
            df = pd.read_csv(dataset_path)
            print("✅ Dataset loaded.")
            return df
        except FileNotFoundError:
            print(f"⚠️ {dataset_path} not found. Running full MLflow pipeline...")
            result = subprocess.run(
                [
                    "mlflow", "run", ".", "-e", "pipeline", "--env-manager=local",
                    "-P", f"processed_dir={processed_dir}"
                ],
                capture_output=True, text=True, encoding="utf-8", errors="replace"
            )
            print(result.stdout)
            if result.returncode != 0:
                print("❌ Full MLflow pipeline failed.")
                raise RuntimeError("Pipeline execution failed.")
            if os.path.exists(dataset_path):
                print("✅ Dataset generated and loaded.")
                return pd.read_csv(dataset_path)
            else:
                raise FileNotFoundError(f"Dataset still not found at {dataset_path}
    else:
        # Step-by-step pipeline execution
        step_cmds = []
        for step in steps:
            if step == "generate":
                cmd = [
                    "mlflow", "run", ".", "-e", "generate", "--env-manager=local"
                ]
                if alt_config:
                    cmd.extend(["-P", f"config={alt_config}"])
                step_cmds.append(("Generate", cmd))
            elif step == "prepare":
                cmd = [
                    "mlflow", "run", ".", "-e", "prepare", "--env-manager=local",
                    "-P", f"processed_dir={processed_dir}"
                ]
                step_cmds.append(("Prepare", cmd))
            elif step == "train-both":
                step_cmds.append(("Train Both", ["mlflow", "run", ".", "-e", "train
            else:
                print(f"⚠️ Unknown step: {step}")

        for name, cmd in step_cmds:
            print(f"\n--- Running: {name} ---\n{' '.join(cmd)}\n")
            result = subprocess.run(cmd, capture_output=True, text=True, encoding="
            print(result.stdout)
            if result.returncode != 0:
                print(f"❌ Step '{name}' failed. Check the output above.")
                break
            else:
                print(f"✅ Step '{name}' completed.\n")

        # Reload dataset after step execution if it exists
        if os.path.exists(dataset_path):
            return pd.read_csv(dataset_path)
        else:
            print("⚠️ Dataset not found after pipeline steps.")
            return None


def calculate_presence_stats(df):
    """Calculate asset presence counts and percentages across Inventory and IPAM.""
    total_assets = len(df)
    present_inventory = (df["missing_in_inventory"] == 0).sum()
    present_ipam = (df["missing_in_ipam"] == 0).sum()
    present_all = ((df["missing_in_inventory"] == 0) & (df["missing_in_ipam"] == 0)

    return {
        "total_assets": total_assets,
        "present_inventory": present_inventory,
        "pct_inventory": present_inventory / total_assets * 100,
        "present_ipam": present_ipam,
        "pct_ipam": present_ipam / total_assets * 100,
        "present_all": present_all,
        "pct_all": present_all / total_assets * 100
    }


def display_presence_summary(stats, scenario_name):
    """Display a quick summary of asset presence counts and percentages."""
    print(f"\n=== {scenario_name} Presence Summary ===")
    print(f"Total Observability Assets: {stats['total_assets']:,}")
    print(f"Present in Inventory: {stats['present_inventory']:,} ({stats['pct_inven
    print(f"Present in IPAM: {stats['present_ipam']:,} ({stats['pct_ipam']:.1f}%)")
    print(f"Present in BOTH: {stats['present_all']:,} ({stats['pct_all']:.1f}%)")

    summary = pd.DataFrame({
        "Metric": ["Present in Inventory", "Present in IPAM", "Present in BOTH"],
        "Count": [stats["present_inventory"], stats["present_ipam"], stats["present
        "Percent": [stats["pct_inventory"], stats["pct_ipam"], stats["pct_all"]]
    })
    display(summary)


def run_completeness_test(present_both, total_assets, threshold=0.75, alpha=0.05):
    stat, p_value = sm.stats.proportions_ztest(
        count=present_both,
        nobs=total_assets,
        value=threshold,
        alternative="larger"
    )
    return stat, p_value, p_value <= alpha
```

```python
def evaluate_completeness(stats, scenario_name):
    """Run and display the completeness statistical test in a clean format."""
    z_stat, p_value, significant = run_completeness_test(stats["present_all"], stat
    result_text = "✅ Reject H₀ – completeness is statistically significant." if s

    display(Markdown(f"""
### Completeness Statistical Test ({scenario_name})

| Metric               | Value                |
|----------------------|----------------------|
| Null Hypothesis (H₀) | Completeness ≤ 75%   |
| Alternative (H₁)     | Completeness > 75%   |
| Observed Rate        | {stats['pct_all']:.2f}% |
| Z-statistic          | {z_stat:.4f}        |
| P-value              | {p_value:.4e}       |
| Alpha (α)            | 0.05               |
| Result               | {result_text}       |
"""))


# define a function to evaluate model performance
def evaluate_model(report_path, model_name, benchmark_f1=0.80):
    """Evaluate model performance against the success benchmark."""
    if not os.path.exists(report_path):
        return {
            "model": model_name,
            "f1_score": None,
            "accuracy": None,
            "result": f"⚠️ No report found for {model_name}"
        }

    with open(report_path, "r") as f:
        report = json.load(f)

    f1_score = report["weighted avg"]["f1-score"]
    accuracy = report["accuracy"]
    result = "✅ Meets benchmark" if f1_score >= benchmark_f1 else "❌ Below bench

    return {
        "model": model_name,
        "f1_score": f1_score,
        "accuracy": accuracy,
        "result": result
    }


def format_metric(value, percent=False):
    """Safely format metrics for display."""
    if value is None:
        return "N/A"
    return f"{value:.2%}" if percent else f"{value:.2f}"


def evaluate_models(inventory_report, ipam_report, scenario_name=None):
    """Evaluate and display predictive model performance in a clean table format.""
    inventory_eval = evaluate_model(inventory_report, "Inventory Model")
    ipam_eval = evaluate_model(ipam_report, "IPAM Model")

    scenario_title = f" ({scenario_name})" if scenario_name else ""

    display(Markdown(f"""
### Predictive Model Evaluation{scenario_title}

| Model             | Accuracy | Weighted F1-Score | Result            |
|-------------------|----------|-------------------|-------------------|
| {inventory_eval['model']} | {format_metric(inventory_eval['accuracy'], percent=Tr
| {ipam_eval['model']}      | {format_metric(ipam_eval['accuracy'], percent=True)}

**Benchmark:** F1-Score ≥ 0.80 required for success.
"""))


def display_report_images(scenario_name):
    """Display generated report images from the pipeline."""
    reports_dir = "reports"
    image_extensions = ('.png', '.jpg', '.jpeg', '.gif')
    found_images = []

    for root, _, files in os.walk(reports_dir):
        for file in files:
            if file.lower().endswith(image_extensions):
                found_images.append(os.path.join(root, file))

    if found_images:
        display(Markdown(f"### Generated Report Images ({scenario_name})"))
        for img_path in found_images:
            rel_path = os.path.relpath(img_path, reports_dir)
            display(Markdown(f"**{rel_path}**"))
            display(Image(filename=img_path))
    else:
        print(f"No report images found in '{reports_dir}' for {scenario_name}.")


def display_conclusion(stats, scenario_name, completeness_significant, inventory_ev
    """Generate and display a comprehensive conclusion summary for a scenario."""
    meets_threshold = stats['pct_all'] >= 75
    threshold_text = "meets" if meets_threshold else "does not meet"
    significance_text = (
        "is statistically significant" if completeness_significant else "is not sta
    )

    inv_model_text = "met" if inventory_eval["f1_score"] and inventory_eval["f1_sco
    ipam_model_text = "met" if ipam_eval["f1_score"] and ipam_eval["f1_score"] >= 0

    conclusion_md = f"""
## Conclusion ({scenario_name})

The analysis confirms that the original asset presence rate across systems **{thres

Out of **{stats['total_assets']:,}** observability assets:
```

```
- **{stats['present_inventory']:,}** ({stats['pct_inventory']:.1f}%) were found in
- **{stats['present_ipam']:,}** ({stats['pct_ipam']:.1f}%) were found in IPAM.
- **{stats['present_all']:,}** ({stats['pct_all']:.1f}%) were present in both syste

Model performance evaluation:
- The Inventory model **{inv_model_text}** the benchmark (F1 ≥ 0.80).
- The IPAM model **{ipam_model_text}** the benchmark (F1 ≥ 0.80).

"""
    if key_features:
        conclusion_md += f"Key features driving missingness include: **{', '.join(k

    conclusion_md += """Beyond validating data completeness, these insights enable
on specific processes, automation, or staff actions most likely to cause data gaps.
This data-driven approach not only supports immediate project goals but also lays t
long-term improvements in asset data quality and system reliability.
"""
    display(Markdown(conclusion_md))
```

In [4]:

```
# Reset the pipeline (cleans data, mlruns, models, reports)
reset_pipeline()
```

```
🔄 Cleaning up pipeline artifacts...
🧹 Removed directory: data
🧹 Removed directory: mlruns
🧹 Removed directory: models
🧹 Removed directory: reports
⚠️ Directory not found: __pycache__
✅ Cleanup complete.
```

In [5]:

```
display_config(config_path)
```

Contents of `config/generation_params.json`:

```
{
    "IPAM_REGION_MISSING_PROBS": {
        "northeast": 0.3,
        "northwest": 0.01,
        "central": 0.01,
        "east": 0.02,
        "west": 0.05,
        "southeast": 0.03,
        "southwest": 0.01
    },
    "INVENTORY_MODEL_MISSING_PROBS": {
        "ISR4431": 0.5,
        "SRX345": 0.6,
        "ETX-2": 0.4,
        "MX204": 0.01,
        "NCS540": 0.05,
        "7750 SR-1": 0.01,
        "7280R": 0.03,
        "FSP3000": 0.1,
        "FSP150": 0.1,
        "QFX5120": 0.05,
        "7050X3": 0.02,
        "Catalyst9300": 0.03
    },
    "DEFAULT_MODEL_FAILURE_PROB": 0.1,
    "DEFAULT_REGION_FAILURE_PROB": 0.1
}
```

In [6]:

```
# Load the dataset for analysis, if it is not present, trigger a mlflow run using t
df = run_pipeline(dataset_path)
```

```
⚠️ data/processed/labeled_asset_dataset_enriched.csv not found. Running full MLflow
pipeline...
[DEBUG] Pipeline received config: config/generation_params.json
✅ Enriched dataset written to: data/processed\labeled_asset_dataset_enriched.csv
--- Model Report ---
              precision    recall  f1-score   support

           0       0.91      0.97      0.94      1966
           1       0.59      0.32      0.41       284

    accuracy                           0.89      2250
   macro avg       0.75      0.64      0.67      2250
weighted avg       0.87      0.89      0.87      2250

--- Model Report ---
              precision    recall  f1-score   support

           0       0.93      1.00      0.96      2103
           1       0.00      0.00      0.00       147

    accuracy                           0.93      2250
   macro avg       0.47      0.50      0.48      2250
weighted avg       0.87      0.93      0.90      2250


✅ Dataset generated and loaded.
```

In [7]:
```
# Default scenario stats
default_stats = calculate_presence_stats(df)
```

In [8]:
```
display_presence_summary(default_stats, "Default Scenario")
```

```
=== Default Scenario Presence Summary ===
Total Observability Assets: 11,246
Present in Inventory: 9,826 (87.4%)
Present in IPAM: 10,512 (93.5%)
Present in BOTH: 9,171 (81.5%)
```

	Metric	Count	Percent
0	Present in Inventory	9826	87.373288
1	Present in IPAM	10512	93.473235
2	Present in BOTH	9171	81.548995

In [9]:
```
evaluate_completeness(default_stats, "Default Scenario")
```

Completeness Statistical Test (Default Scenario)

Metric	Value
Null Hypothesis (H_0)	Completeness ≤ 75%
Alternative (H_1)	Completeness > 75%
Observed Rate	81.55%
Z-statistic	17.9042
P-value	5.4699e-72
Alpha (α)	0.05
Result	✅ Reject H_0 – completeness is statistically significant.

```
In [10]: # Save significance result for use in conclusion
         _, _, default_completeness_significant = run_completeness_test(
             default_stats["present_all"], default_stats["total_assets"]
         )
```

```
In [11]: # Evaluate models
         inventory_eval = evaluate_model("reports/inventory/inventory_classification_report.
         ipam_eval = evaluate_model("reports/ipam/ipam_classification_report.json", "IPAM Mo

         evaluate_models("reports/inventory/inventory_classification_report.json",
                         "reports/ipam/ipam_classification_report.json",
                         "Default Scenario")
```

Predictive Model Evaluation (Default Scenario)

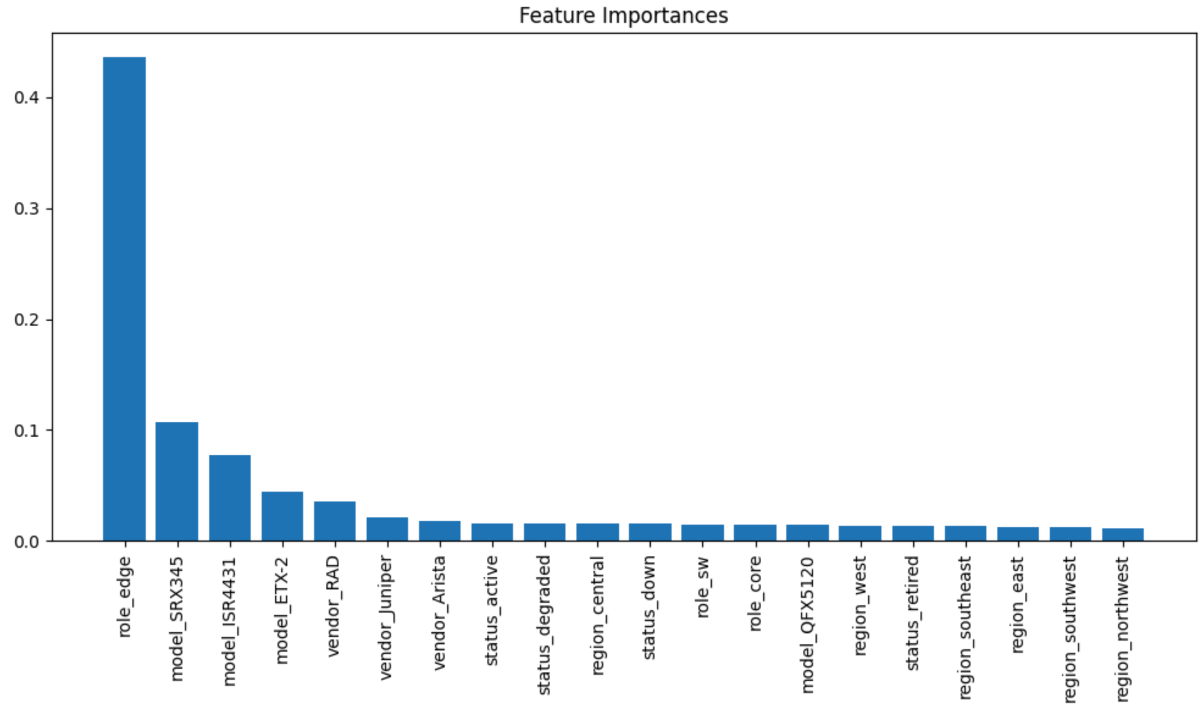
Model	Accuracy	Weighted F1-Score	Result
Inventory Model	88.58%	0.87	✅ Meets benchmark
IPAM Model	93.16%	0.90	✅ Meets benchmark

Benchmark: F1-Score ≥ 0.80 required for success.

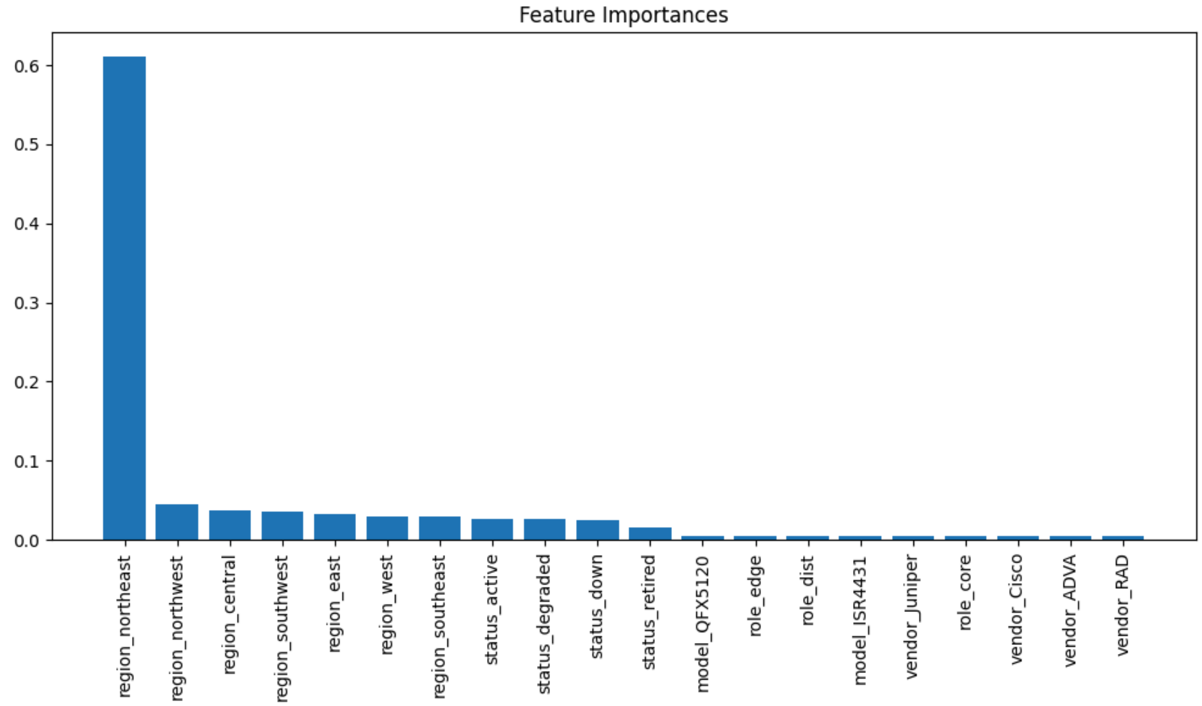
```
In [12]: display_report_images("Default Scenario")
```

Generated Report Images (Default Scenario)

inventory\inventory_feature_importance.png



ipam\ipam_feature_importance.png



Conclusion

In [23]:
```
display_conclusion(
    default_stats,
    "Default Scenario",
    completeness_significant=default_completeness_significant,
    inventory_eval=inventory_eval,
    ipam_eval=ipam_eval,
    key_features=["region", "role"]
)
```

Conclusion (Default Scenario)

The analysis confirms that the original asset presence rate across systems **meets** the 75% threshold and is statistically significant based on the statistical test.

Out of **11,246** observability assets:

- **9,821** (87.3%) were found in the Inventory system.
- **10,515** (93.5%) were found in IPAM.
- **9,178** (81.6%) were present in both systems.

Model performance evaluation:

- The Inventory model **met** the benchmark (F1 ≥ 0.80).
- The IPAM model **met** the benchmark (F1 ≥ 0.80).

Key features driving missingness include: **region, role**.

Beyond validating data completeness, these insights enable the organization to focus audit efforts on specific processes, automation, or staff actions most likely to cause data gaps. This data-driven approach not only supports immediate project goals but also lays the groundwork for long-term improvements in asset data quality and system reliability.

Analysis demonstrating alternative data generation scenarios

To validate that our ML model would make different predictions given different failures, we ran an alternative config to validate

In [14]:
```
# display_config(alt_config)
display_config(alt_config)
```

Contents of `config/alt_scenario_generation_params.json`:

```
{
    "IPAM_REGION_MISSING_PROBS": {
        "northeast": 0.01,
        "northwest": 0.01,
        "central": 0.01,
        "east": 0.02,
        "west": 0.45,
        "southeast": 0.03,
        "southwest": 0.01
    },
    "INVENTORY_MODEL_MISSING_PROBS": {
        "ISR4431": 0.01,
        "SRX345": 0.03,
        "ETX-2": 0.02,
        "MX204": 0.01,
        "NCS540": 0.05,
        "7750 SR-1": 0.01,
        "7280R": 0.03,
        "FSP3000": 0.1,
        "FSP150": 0.87,
        "QFX5120": 0.91,
        "7050X3": 0.02,
        "Catalyst9300": 0.03
    },
    "DEFAULT_MODEL_FAILURE_PROB": 0.1,
    "DEFAULT_REGION_FAILURE_PROB": 0.1
}
```

In [16]:

```
# Run the pipeline for the alternative scenario
alt_df = run_pipeline(
    dataset_path="data/processed/labeled_asset_dataset_enriched.csv",
    alt_config="config/alt_scenario_generation_params.json",
    steps=["generate", "prepare", "train-both"]
)
```

```
--- Running: Generate ---
mlflow run . -e generate --env-manager=local -P config=config/alt_scenario_generation_params.json
```

```
✅ Step 'Generate' completed.


--- Running: Prepare ---
mlflow run . -e prepare --env-manager=local -P processed_dir=data/processed

✅ Enriched dataset written to: data/processed\labeled_asset_dataset_enriched.csv

✅ Step 'Prepare' completed.


--- Running: Train Both ---
mlflow run . -e train-both --env-manager=local

--- Model Report ---
              precision    recall  f1-score   support

           0       0.97      0.97      0.97      1830
           1       0.88      0.88      0.88       420

    accuracy                           0.96      2250
   macro avg       0.93      0.93      0.93      2250
weighted avg       0.96      0.96      0.96      2250

--- Model Report ---
              precision    recall  f1-score   support

           0       0.93      0.98      0.95      2066
           1       0.41      0.16      0.23       184

    accuracy                           0.91      2250
   macro avg       0.67      0.57      0.59      2250
weighted avg       0.89      0.91      0.89      2250


✅ Step 'Train Both' completed.
```

In [17]:

```python
# Calculate presence statistics
alt_stats = calculate_presence_stats(alt_df)
```

In [18]:

```python
# Display quick summary
display_presence_summary(alt_stats, "Alternative Scenario")
```

```
=== Alternative Scenario Presence Summary ===
Total Observability Assets: 11,246
Present in Inventory: 9,148 (81.3%)
Present in IPAM: 10,327 (91.8%)
Present in BOTH: 8,395 (74.6%)
```

	Metric	Count	Percent
0	Present in Inventory	9148	81.344478
1	Present in IPAM	10327	91.828206
2	Present in BOTH	8395	74.648764

In [19]:

```
# Evaluate completeness (statistical test)
evaluate_completeness(alt_stats, "Alternative Scenario")
```

Completeness Statistical Test (Alternative Scenario)

Metric	Value
Null Hypothesis (H_0)	Completeness ≤ 75%
Alternative (H_1)	Completeness > 75%
Observed Rate	74.65%
Z-statistic	-0.8562
P-value	8.0406e-01
Alpha (α)	0.05
Result	❌ Fail to reject H_0 – completeness is not statistically significant.

In [20]:

```
# Save significance result for use in conclusion
_, _, alt_completeness_significant = run_completeness_test(
    alt_stats["present_all"],
    alt_stats["total_assets"]
)
```

In [21]:

```
# Evaluate models
inventory_eval_alt = evaluate_model("reports/inventory/inventory_classification_rep
ipam_eval_alt = evaluate_model("reports/ipam/ipam_classification_report.json", "IPA


evaluate_models(
    "reports/inventory/inventory_classification_report.json",
    "reports/ipam/ipam_classification_report.json",
    "Alternative Scenario"
)
```

Predictive Model Evaluation (Alternative Scenario)

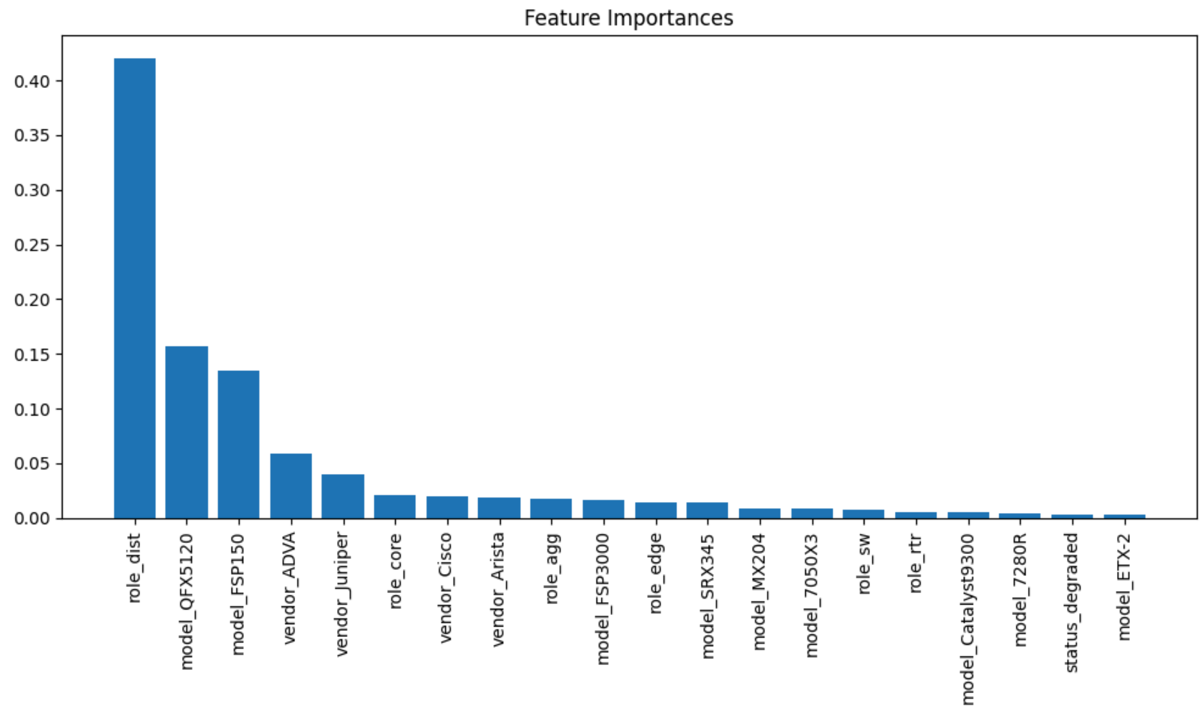
Model	Accuracy	Weighted F1-Score	Result
Inventory Model	95.56%	0.96	✅ Meets benchmark
IPAM Model	91.24%	0.89	✅ Meets benchmark

Benchmark: F1-Score ≥ 0.80 required for success.

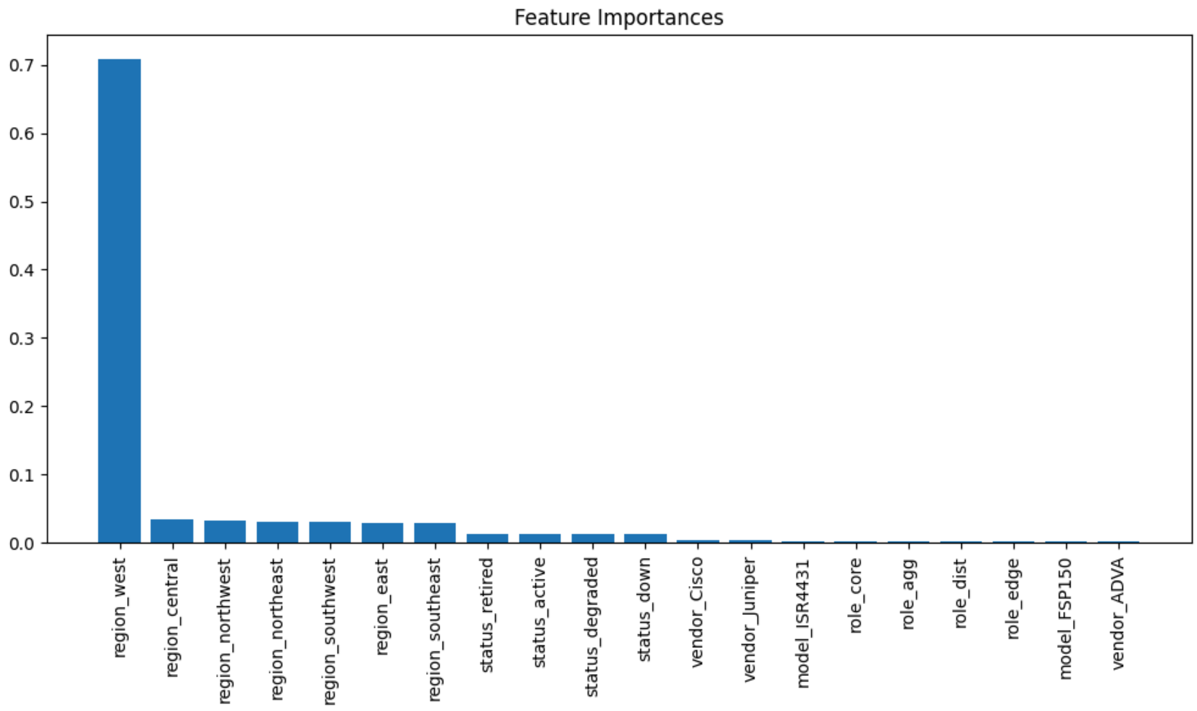
In [22]:
```
# Display generated report images
display_report_images("Alternative Scenario")
```

Generated Report Images (Alternative Scenario)

inventory\inventory_feature_importance.png



ipam\ipam_feature_importance.png



In [24]:

```
# Display conclusion for alternative scenario
display_conclusion(
    alt_stats,
    "Alternative Scenario",
    completeness_significant=alt_completeness_significant,
    inventory_eval=inventory_eval_alt,
    ipam_eval=ipam_eval_alt,
    key_features=["region", "role"]
)
```

Conclusion (Alternative Scenario)

The analysis confirms that the original asset presence rate across systems **does not meet** the 75% threshold and is not statistically significant based on the statistical test.

Out of **11,246** observability assets:

- **9,139** (81.3%) were found in the Inventory system.
- **10,325** (91.8%) were found in IPAM.
- **8,387** (74.6%) were present in both systems.

Model performance evaluation:

- The Inventory model **met** the benchmark (F1 ≥ 0.80).
- The IPAM model **met** the benchmark (F1 ≥ 0.80).

Key features driving missingness include: **region, role**.

Beyond validating data completeness, these insights enable the organization to focus audit efforts on specific processes, automation, or staff actions most likely to cause data gaps. This data-driven approach not only supports immediate project goals but also lays the groundwork for long-term improvements in asset data quality and system reliability.