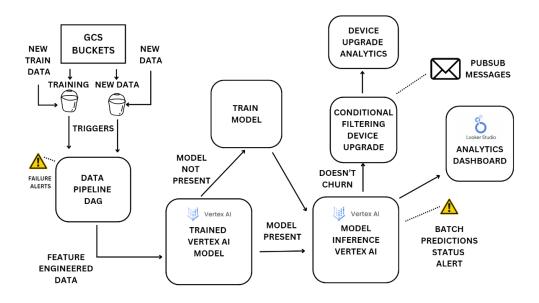
Telecom Customer Churn and Mobile Device Upgrade Prediction Project Workflow and Screenshots



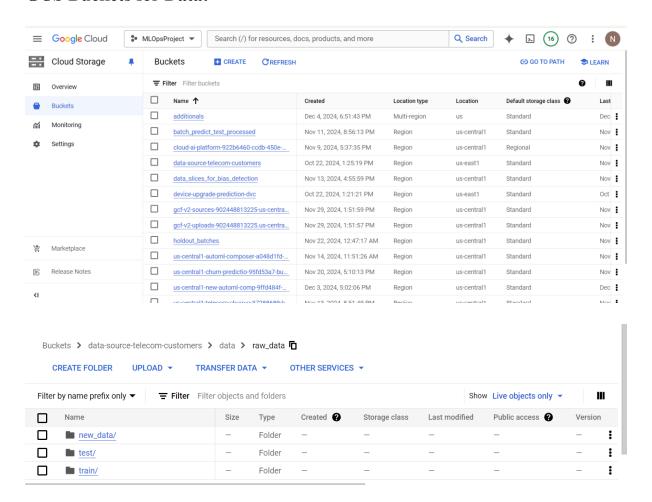
Business Use Case: Telecom companies have a pressing need to analyze dynamic customer behavior in order to send timely offers and prevent customer churn. This project addresses the need by designing a GCP based end-to-end pipeline for predicting customer churn and filtering customers who would upgrade their device to send notifications.

As the telecom companies receive customer data in new **batches**, this pipeline gets triggered to perform churn prediction, device upgrade estimation, and real-time customer analytics on interactive dashboards. We designed an interconnected DAG system with triggers to orchestrate the flow as new data gets ingested.

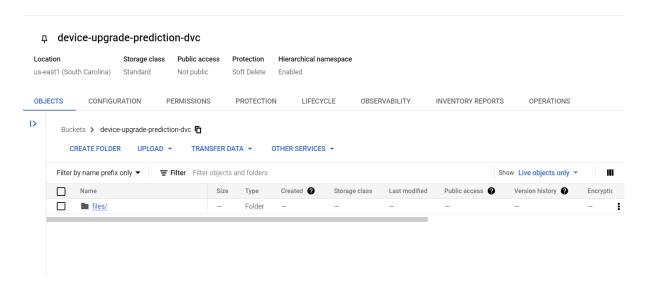
GCP Project Service Account Permissions:



GCS Buckets for Data:



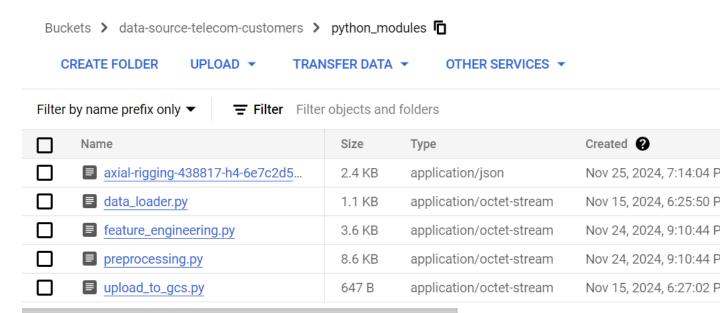
DVC integration for data version control:



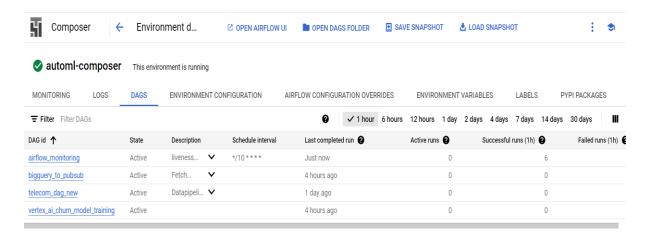
DVC logs cache files stored in a bucket.

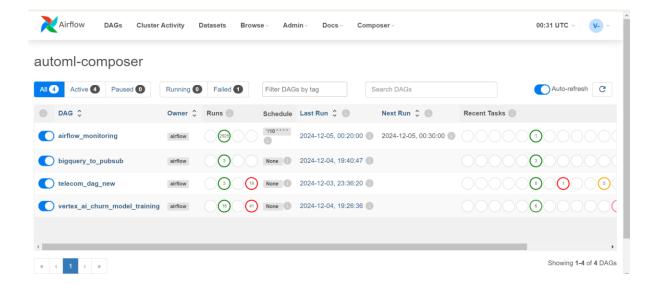
Python modules loaded to GCS:

Custom made python modules that are used by DAG tasks. DAG access these modules from the bucket.

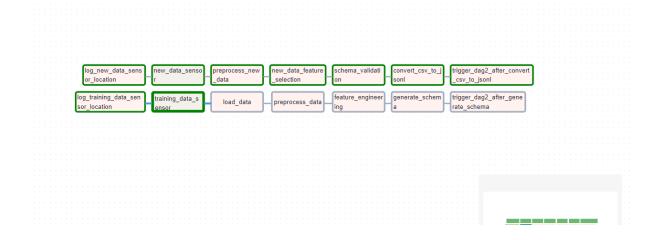


DAGs in Composer environment:

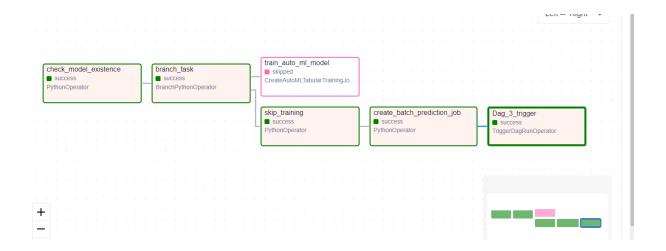




Data Pipeline DAG - gets triggered with incoming new data

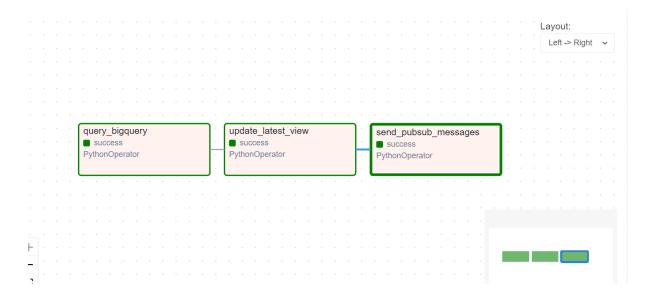


Vertex AI DAG - gets triggered when data DAG runs successfully; makes a call to Vertex AI model (Inference if model is present, training if model is not present already)

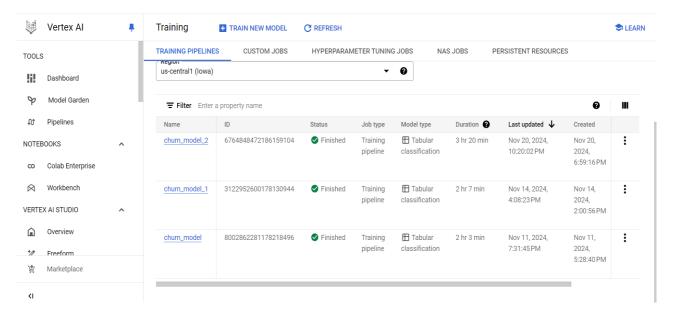


Front end DAG - gets triggered when vertex AI DAG runs successfully; Stores

predictions in Big Query, updates Looker dashboard, filters customers likely to upgrade and sends messages Pub/Sub

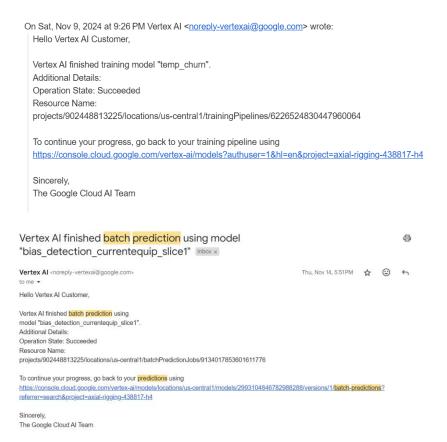


Vertex AI model:



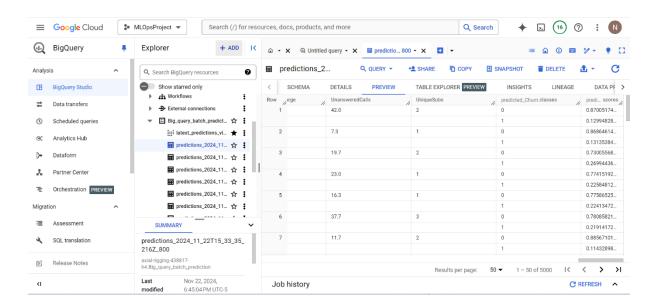
Latest and best model version – churn_model_2.

Notifications: Email alerts received after training completion and every batch prediction completion.

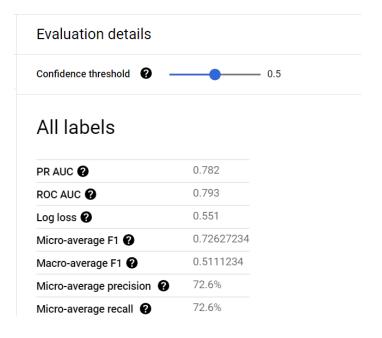


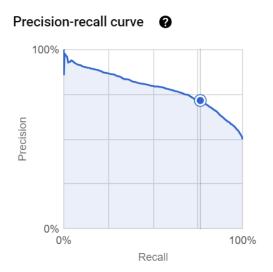
Vertex AI model inferences stored on Big Query for every batch:

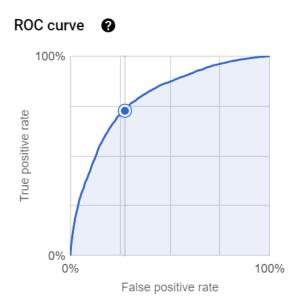
```
# Task: Create batch prediction job
def create batch prediction job(**kwargs):
    log = get_task_logger("create_batch_prediction_job")
    try:
        model name = kwargs['ti'].xcom pull(task ids='check model existence', key='model name')
        if not model name:
            raise ValueError("No model found for batch prediction.")
        log.info("Initializing Vertex AI platform for batch prediction...")
        aiplatform.init(project=PROJECT_ID, location=LOCATION)
        gcs_input = f"gs://{BUCKET_NAME}/latest_best_features_for_churn.jsonl"
        bigquery_output_prefix = "axial-rigging-438817-h4.Big_query_batch_prediction"
        log.info("Creating batch prediction job...")
        batch_prediction_job = aiplatform.BatchPredictionJob.create(
            job_display_name="batch_prediction_job",
            model name=model name,
            gcs_source=gcs_input,
            predictions_format="bigquery",
            starting_replica_count=10,
            max_replica_count=20,
            machine_type="c2-standard-30",
            bigquery_destination_prefix=bigquery_output_prefix
```



Model Performance:



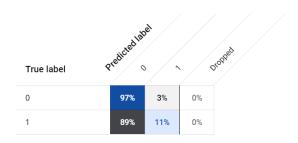




Confusion matrix



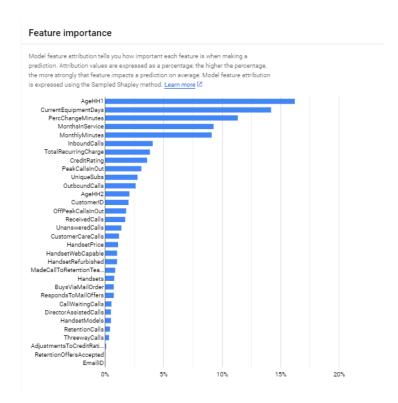
A confusion matrix shows how the model classified each label in the evaluation dataset. The blue, bold cells indicate a correct prediction. A data item is moved to the dropped column if it does not meet the confidence threshold for any label.



Feature Sensitivity Analysis:

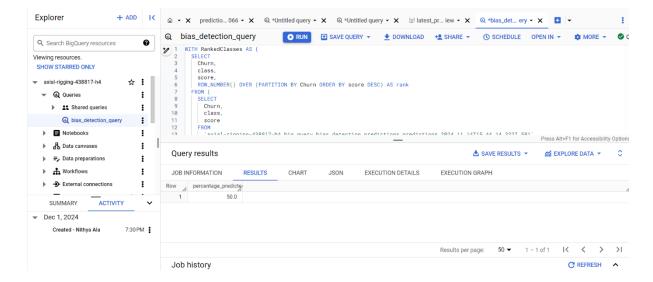
Explanations stored in big query

prediction	ons_2	Q QUERY •	* SHARE	COPY	■ SNAPSHOT	TOTAL		C REFRESI
CHEMA	DETAILS	PREVIEW	TABLE EXPLORER		INSIGHTS	LINEAGE	DATA PROFILE	DATA QUALITY
	Neteritionoans		0111110	NOLLABLE				
	RetentionOffers	Accepted	STRING	NULLABLE		-	-	-
	ThreewayCalls		STRING	NULLABLE		-	-	-
	TotalRecurringC	Charge	STRING	NULLABLE		-	-	-
	UnansweredCal	ls	STRING	NULLABLE		-	-	-
	UniqueSubs		STRING	NULLABLE		-	-	-
	explanation		RECORD	NULLABLE		-	-	-
	▼ attribution	ons	RECORD	REPEATED		-	-	-
	▶ fe	atureAttributions	RECORD	NULLABLE		-	-	-
	OI	utputDisplayName	STRING	NULLABLE		-	-	-
□ →	predicted_Chur	n	RECORD	NULLABLE		-	-	-

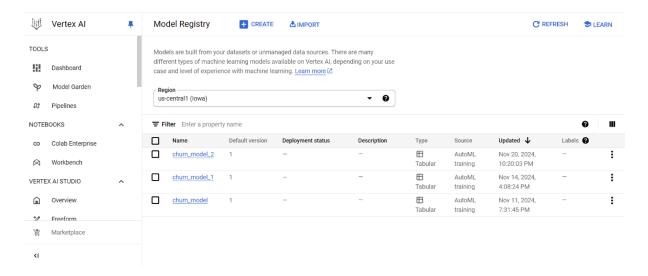


Bias Detection:

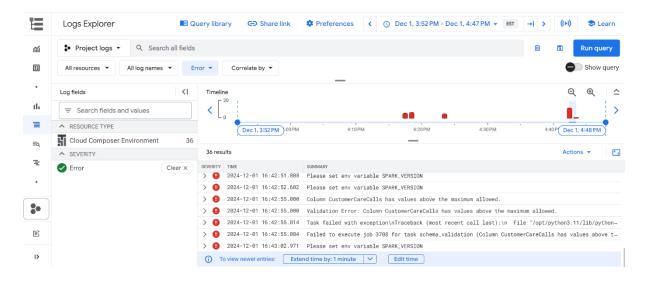
Bias detection performed on the most relevant column 'CurrentEquipmentDays'. Data sliced into 3 slices, predictions stored in big query and queried to analyze the model's performance on different slices. The model performance is similar for all slices so no bias was detected.



Model Registry:



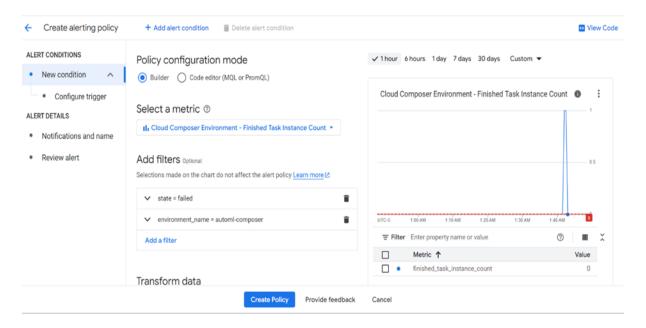
Logging and Alerts:

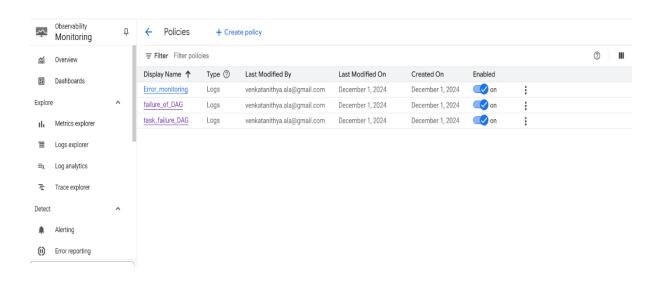


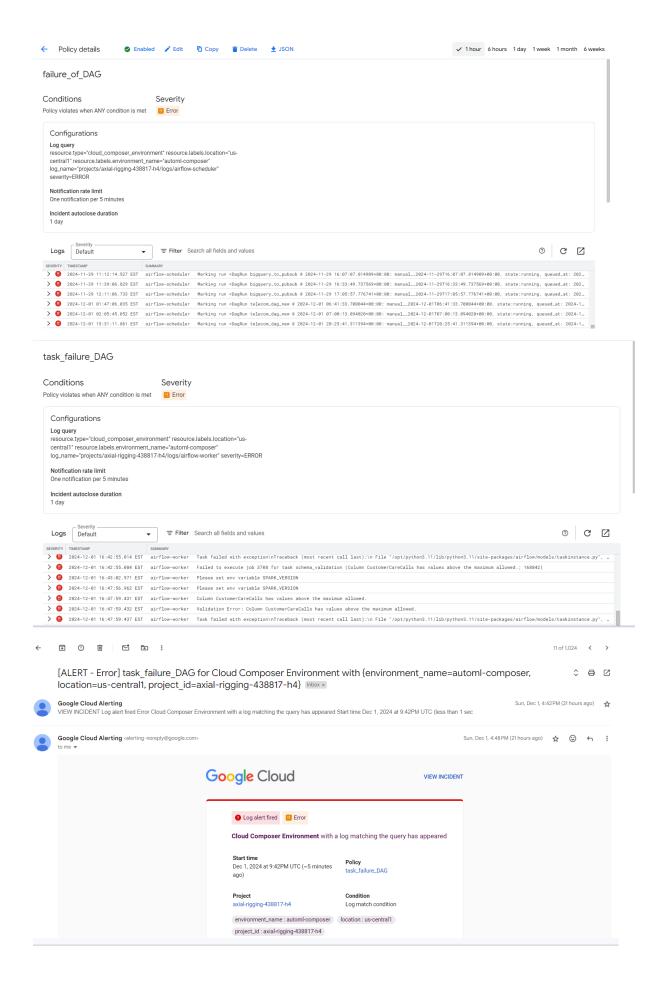
Utilizing log explorer for analyzing logs.

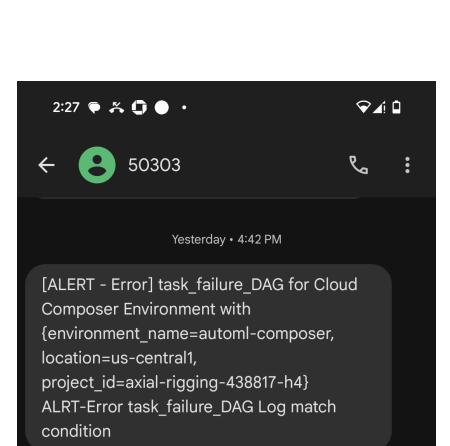
Alert policies set up to monitor task failures and DAG failures.

Email and SMS alerts set up.









Unread

[ALERT - Error] task_failure_DAG for Cloud Composer Environment with {environment_name=automl-composer, location=us-central1, project_id=axial-rigging-438817-h4} ALRT-Error task_failure_DAG Log match condition

[ALERT - Error] failure_of_DAG for Cloud Composer Environment with {environment_name=automl-composer, location=us-central1, project_id=axial-rigging-438817-h4} ALRT-Error failure_of_DAG Log match condition

4:48 PM





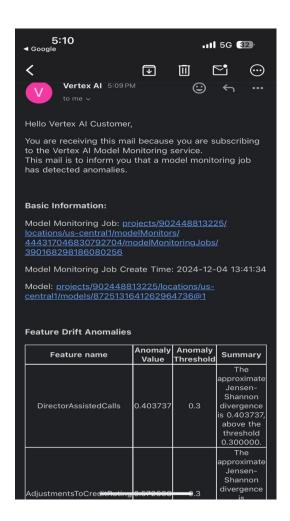
Text message





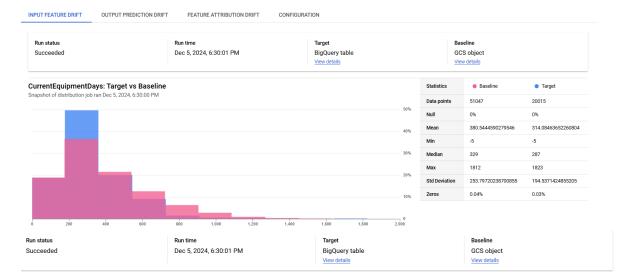
Model Monitoring:

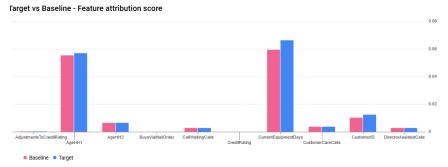
Model monitoring jobs set up and email alerts set up.



Drift detection jobs set up for analyzing feature drift, email alerts set up if drift score goes over the threshold.

Features	Baseline	Target	Alerts	Drift score	Threshold	Metric
 AdjustmentsToCreditRating 	II	II		0.58344	0.3	Jensen-Shannon
AgeHH1	Hama.		-	0.00102	0.3	Jensen-Shannon
AgeHH2	H	H	-	0.00532	0.3	Jensen-Shannon
 BuysViaMailOrder 	h	h	-	0.02425	0.3	L-Infinity
 CallWaitingCalls 	II	II	-	0.03946	0.3	Jensen-Shannon
 CreditRating 	lu	h		0.49963	0.3	L-Infinity
 CurrentEquipmentDays 		ob	-	0.02856	0.3	Jensen-Shannon
 CustomerCareCalls 	II	II	-	0.19007	0.3	Jensen-Shannon
CustomerID			-	0.13037	0.3	Jensen-Shannon
 DirectorAssistedCalls 	II	II		0.3237	0.3	Jensen-Shannon
EmailID	li.	li .	-	0.16255	0.3	L-Infinity
 HandsetModels 	II	II	-	0.0295	0.3	Jensen-Shannon
HandsetPrice	********			0.61517	0.3	Jensen-Shannon
 HandsetRefurbished 	I.	I.	-	0.01126	0.3	L-Infinity
 HandsetWebCapable 	I.	I.	-	0.04381	0.3	L-Infinity
Handsets	II	II	-	0.05549	0.3	Jensen-Shannon





Features	Alerts	Score	Baseline score	Deviation	Threshold
AdjustmentsToCreditRating	-	0.00029	0.00031	-0.00002	0.3
AgeHH1	-	0.057	0.05538	0.00162	0.3
AgeHH2	-	0.00648	0.00665	-0.00017	0.3
BuysViaMailOrder	-	0	0		0.3
CallWaitingCalls	-	0.00269	0.00268	0.00001	0.3
CreditRating	-	0	0		0.3
CurrentEquipmentDays	_	0.06634	0.05942	0.00692	0.3

Retraining criteria:

Our architecture supports **on-demand retraining**, triggered by the addition of new data to the 'training data' bucket. The decision to include new data for retraining is informed by schema validation and anomaly detection tasks, which are part of the DAGs processing the incoming data. We also consider input feature drift and model performance (model drift) to prepare new training data and place it in the designated bucket. This action automatically triggers the training DAG, initiating the retraining process. By centralizing operations on GCP with storage buckets, Cloud Composer, and Vertex AI, our system maintains streamlined and automated workflows, eliminating the need for traditional CI/CD pipelines.

CI/CD:

We determined that integrating with Git for CI/CD workflows related to code changes is unnecessary for our project as it is fully deployed on Google Cloud Platform (GCP), leveraging Vertex AI's AutoML for model training and predictions. Since Vertex AI AutoML handles the modeling process, no custom model code is required. We have implemented automatic triggers based on incoming data, ensuring that Dataflow pipelines and directed acyclic graphs (DAGs) in Cloud Composer are executed whenever new data is added to the GCP storage buckets. The logic for these DAGs is predefined and fixed, automating the entire workflow without requiring code modifications.

Front End - Looker Analytics Dashboard



Since the telecom companies receive data in big batches, a front end is designed to display analytics of the batches rather than per customer user input-prediction design.