

LRS standards

January 27, 2021

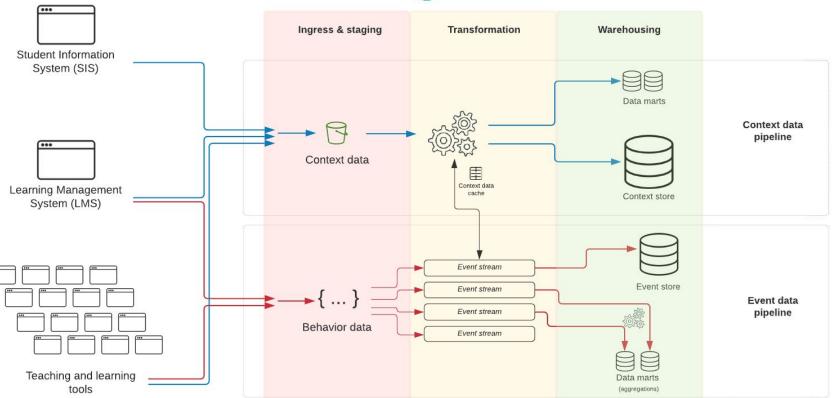
Agenda



2 UDP's mart/hub architecture







Context data

Describe objects (e.g., learners, assignments, modules, outcomes, learning design, course catalog, degree) and relationships relevant to learners, learning environments, and overall academic experience.

- Rich in description
- Relational
- Typically from an ODS
- Suitable for batch processing

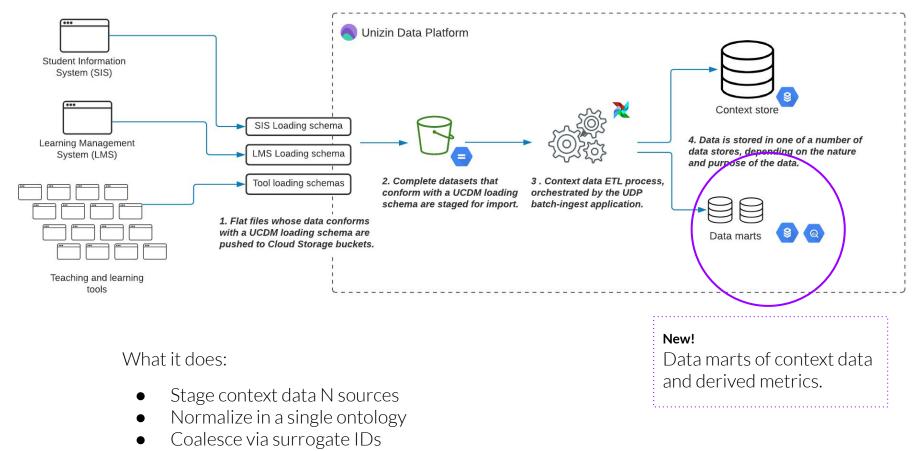
Data standard: UCDM

Behavior data

Describes the discrete actions of instructors, learners, teaching assistants, and even tools themselves in the learning environment

- Thin in description
- Event-driven
- Emitted from apps & APIs
- Suitable for event/signal processing

Data standard: IMS Global Caliper



• Unified presentation & derived marts

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Context data

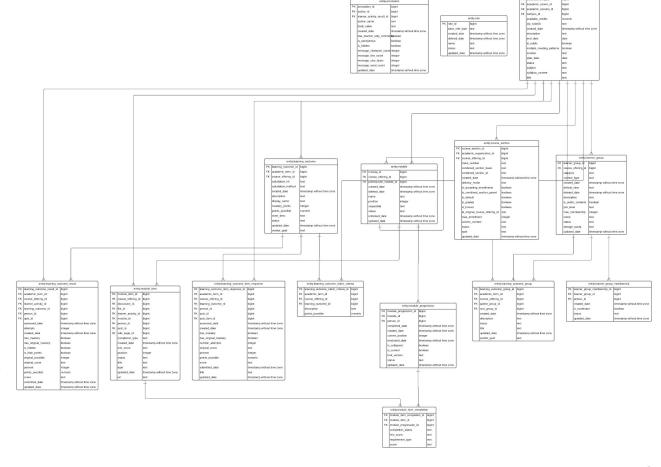
Data dictionary:

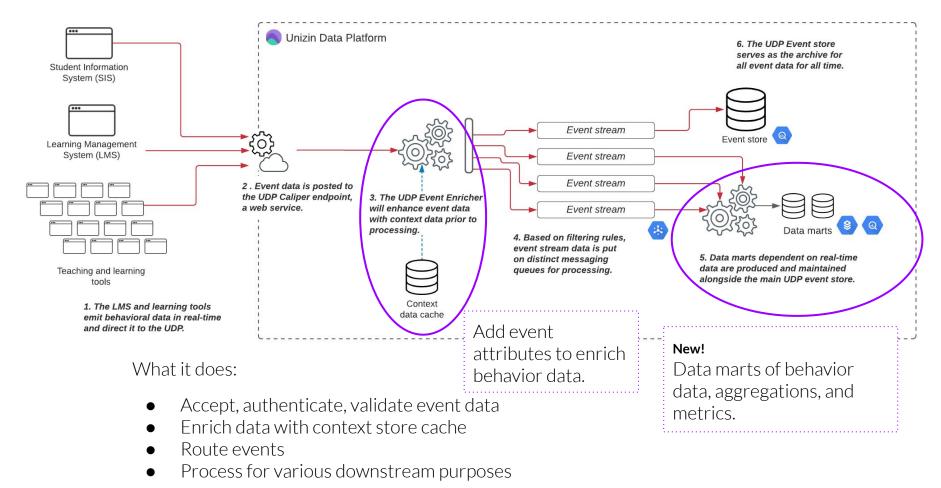
- 70 UCDM entities (primary concepts and tables).
- 800+ elements (attributes)
- Intended to model SIS, LMS, and Learning tool data in ODS

Relational model:

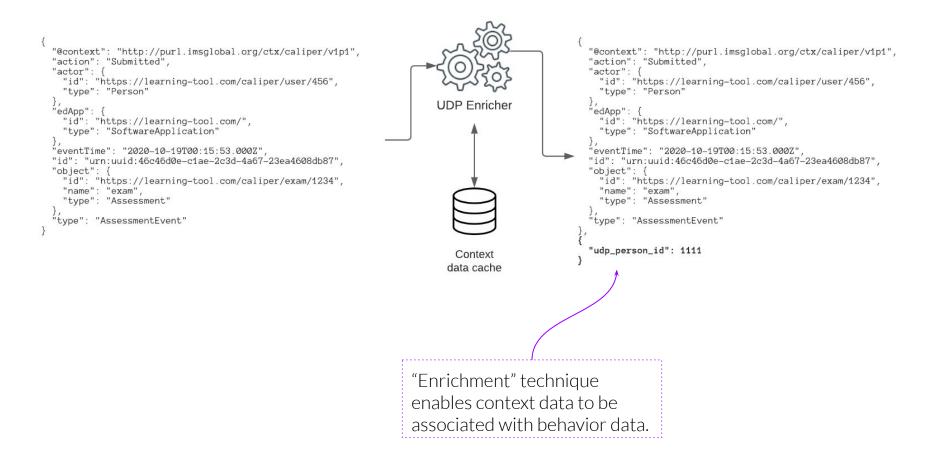
- All entities in a single relational model
- Enables all SIS, LMS, and learning data records to be associated

Visit: https://resources.unizin.org/display/UDP/ Unizin+Common+Data+Model





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Data marts

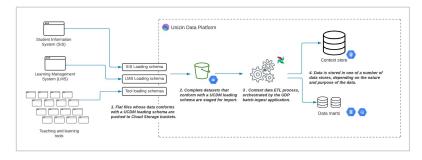
Build off the data pipeline architecture and use context & behavior processing capabilities.

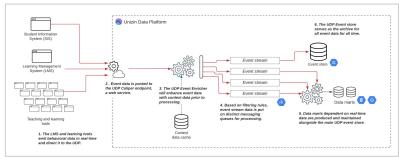
Context data:

• Expand Airflow ETL orchestration to build denormed/narrow data marts

Behavior data:

- Python scripts running in k8s clusters listening to PubSub, performing some compute, writing to a store
- Routing/processing interdependencies, esp. for aggregations
- Mix of real-time and scheduled ETL
- No special tooling yet (e.g., Kafka, Spark)











Events from a single fire hose are routed and then replicated along distinct messaging queues, each dedicated to a particular form of processing. Strong candidate for storing and processing large volumes of data, both scheduled and ad hoc.

We use BigQuery for a variety of event-based data marts and research / ML training datasets.



Kubernetes



Almost all of our event processing logic is captured in small Python scripts that run concurrently and that are deployed in k8s clusters.



Reasonable candidate for particular real-time data marts.

Batch ETL orchestration for our context data pipeline.

Architecting for marts

Divide the broad domain of marts into a handful of dimensions:

- **Grain**: what level of detail is associated with the facts, metrics, measures in the mart?
- Features/metrics: what features, facts, or metrics are expressed for this grain of data?
- Latency/periodicity: how fresh does the mart's data need to be to satisfy its use-cases?
- **Complementarity**: can marts work together to meet use-case requirements (e.g., slowly-changing labels and real-time metrics).

Architecting for persona

Unizin institutions generally need to serve four classes of data stakeholders:

- **Ops/BI reporting staff**: produce timely, actionable reporting and analytics for decision-support.
- Faculty, advising, CTL: consume timely course measures and analytics to drive intervention, teaching insights.
- Researchers: create and/or consume prepared research datasets for regular and ad hoc inquiry.
- **ML practice**: produce datasets to train, and then use, ML models for various classifications.

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Course readiness

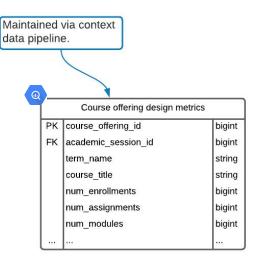
Problem: how do we ensure that all LMS courses are published and available by the start of the term?

Grain: By course offering

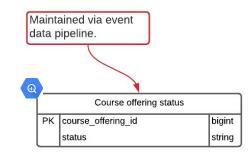
Data's role: provide near real-time insight into unpublished courses that likely ought to be published.

Who: BI, IR, Ops, Faculty/instructors

Latency: < 1 hour



D enormalized mart of course design metrics. Slowly changing data updated every 24 hours via context data ETL.



Simple event-based mart to represent course status. Runs every hour and maintains current course status with < 1hour latency.

Last activity

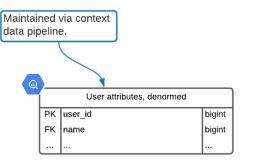
Problem: how do we identify students who may not be interacting in the LMS but ought to be?

Grain: By course offering, by student

Data's role: provide ability to query for students who are lagging, per metrics that are relevant to context, in real-time.

Who: BI, IR, Ops

Latency: < 1 minute



Denormed table of user labels (name, email, etc) used for reporting purposes.

	ained via event bipeline.	
	Last activity	
FK	course_offering_id	bigint
FK	actor_id	bigint
	last_activity	timestamp
	last_navigation_activity	timestamp
	last_media_activity	timestamp
	last_grade_activity	timestamp
	last_assessment_activity	timestam
	last_assignment_activity	timestamp

Table (in postgres) updated every 15 seconds (via upsert) to maintain the last time a student was activity on some particular kind of activity per the Caliper ontology.

Tool launches

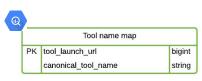
Problem: we have little insight to what LTI tools are used where, how much, and by which departments and courses.

Grain: By course offering, by user, by tool launch event

Data's role: provide near-real time insight into LTI tool usage, measured as a function of launches by users, across the LMS and the institution.

Who: BI, IR, Ops

Latency: < 1 minute



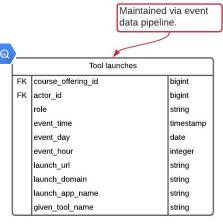
Custom canonical tool name table that is generated and maintained by neither data pipeline.

User attributes, denormed

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PK user id

FK name



Running table (in BigQuery) of every single tool launch, culled from the event data pipeline.

Re-use tables that are		Course offering design metrics	-
already generated for	PK	course_offering_id	bigint
other purposes.	FK	academic_session_id	bigint
		term_name	string
		course_title	string
		num_enrollments	bigint
		num_assignments	bigint
		num_modules	bigint

bigint

bigint

Course grade prediction training/scoring sets

Problem: classify likelihood of a failing grade; confidence must improve as term unfolds.

Grain: By course enrollment

Data's role: beyond demo/test/gpa data, leverage behavioral metrics.

Who: Research, ML practice

Latency: Weekly

Metrics in the feature set:

- By person, by course observations
- Grade/outcomes
- Demo, SES, standardized test
- Term, course, department, etc.
- Performance & behaviors, by week of term, for all activities
- Ahead/behind performance & behaviors, relative to class, for each week of term

https://gitlab.com/unizin/community/unizin-data-platform/iu-bar-cgr

Course to course conditional probability

/*

Problem: we need to provide course recommendations to students to find an optimal pathway.

Grain: By course enrollment

Data's role: leverage historical and outcomes data to train models or provide research data

Who: Research, ML practice

Latency: Every term

Course to course conditional probability				
current_term_order	integer			
current_node_course	bigint			
next_term_order	integer			
next_node_course	bigint			
next_node_given_current_node_percentage	numerical			
student_transition_count	integer			

Mart / Course offering / Course to course conditional probability

Computes the conditional probability that if you took Course A in Term X you will take course B in Term Rank X + 1 (next term).

```
Dependencies:
    * Base / Course offering
    * Base / Course section enrollment
*/
/*
  Every course taken by the student, decorated with the title of the course and
  the rank of the term in their academic career in which they took it.
*/
WITH student course term AS (
  SELECT
  co.title AS course title
  , cse.person id AS person id
  , cse.rank person academic term order asc AS rank person academic term order asc
  FROM
  base.course section enrollment cse
  LEFT JOIN
  base.course offering co USING (course offering id)
  WHERE
  cse.is role student = 1
  AND cse.credits taken > 0
),
/*
  Computes the count of the student population represented in the previously-
  generated table of students and their courses.
total student count AS (
  SELECT
  COUNT(distinct sct.person id) AS total student count
  FROM
  student course term AS sct
),
/*
  Computes the count of students who took the courses by the order of their
  Academic term.
* /
```

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UDP Documentation

We've recently updated our UDP documentation

Intended for a variety of audiences (technical, analytics, research, etc.).

The emerging UDP Data services layer will be documented here, too.

Visit https://resources.unzin.org

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Unizin Data P	Platform – 🗏	•
Q Search	Dashboard	z ^a

V Unizin Data Platform

Key concepts

 Platform overview Data categories

Data models

Loading schemas

Keymap

- V Unizin Common Data Model
- Academic structures (ERD)
- Learners (ERD) Course structures (ERD)
- Course resources (ERD)
- Learner activities (ERD)
- Quizzes (ERD)
- Social (ERD)
- Course outcomes (ERD)
- System overview
- > Context data pipeline
- > Event data pipeline
- V Data integrations > Context data integration
- Event data integration
- SIS data integration
- LMS data integration
- Release Notes
- 2.0.53 All Canvas-native data
- 2.0.47 Additional Canvas Data an...
- 2.0.25 Full SIS 2.0, performance ...
- Miscellaneous
- · Canvas Live Events: from SQS to ...
- · Migrating from UDW to UDP

The content of this macro can only be viewed by users who have logged in.

Unizin Data Platform



The Unizin Data Platform (UDP) is a data platform product that integrates, aggregates, cleans, models, and stores all teaching and learning data into a data lake.

It generates a unified portrait of learners in the context of their learning environments and provides a layer of data services to drive analytics, data science, and research, enabling institutions to build effective data-driven practices at scale.

The UDP supports two data standards: (1) IMS

Global Caliper, (2) Unizin Common Data Model

The Unizin Data Platform (UDP) is a cloud-native, single-tenant architecture solution that integrates and warehouses data from the Student Information System (SIS), Learning Management System (LMS), and LMS-integrated tools,

Data standards

together.

Key concepts

Understand the fundamentals of how the UDP aggregates and normalizes learning data to serve a learning analytics ecosystem. The section describes the key features of the UDP

- Support for IMS Global Caliper
- · UCDM overview and taxonomy

(UCDM). The two data standards are

complementary and enable the UDP to

consolidate all teaching and learning data

UCDM Data dictionary

Data integrations

Understand how to create two kinds of UDP data integrations: context data integrations and behavior data integrations.

Any individual responsible for configuring or creating SIS, LMS, or Learning tool integrations to the UDP will find this section essential.

1. Context data integrations 2. Behavior data integrations 3. SIS data integration 4. LMS data integration

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and the ideas that inform its technical design. If you are new to the UDP, we strongly recommend that you begin with the Key concepts section.

1. Platform overview 2. Data categories 3. Data models 4. Loading schemas 5. Keymap

System overview

The Unizin Data Platform (UDP) is primarily composed of two data pipelines. Each data pipeline creates and maintains the data lakes and data marts that undergird the UDP's data services. There exists one data pipeline for each learning data category integrated by the Unizin Data Platform (context data and behavior data).

1. Context data pipeline 2. Event data pipeline



Thank you

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