Solving Real Business Problems with AI.

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Problem Statement

Over the last five to ten years, we have observed tremendous leaps in machine learning for universal modalities such as vision, language, audio, and video. With approximately twenty lines of code, anyone can download and fine-tune a foundation model to solve arbitrary tasks in these domains because of the extraordinarily accessible high-level abstractions built for these modalities. However, these high-level abstractions are limited exclusively to the problems within and in-between these select few universal modalities (text-to-speech, image-to-video, text-to-audio, image-to-text, text summarization, sentence similarity, etc). The abstractions are only possible because the modalities are universal.

Tabular machine learning is in quite a different spot. In practice, it has not really changed all that much over the last decade. If you ask anyone how they would approach a tabular machine learning problem they will likely recommend a GBM. A gradient boosted decision tree provides excellent results for most tabular machine learning problems. Beyond their spectacular performance, they are intuitive, interpretable, and easy to train. They are able to scale to larger-than-memory datasets with distributed compute and accelerated hardware. GBMs are the undisputed champion for every tabular machine learning problem.

GBMs really are the best solution for actual tabular machine learning. However, I do not think that they are not the correct solution for the majority of the problems in which they are currently utilized. In other words, I strongly believe that the vast majority of machine learning problems that are currently being modeled with GBMs are not actually tabular.

That is a really bold statement that I would like to contextualize with an example:

Suppose you are to train a model to verify the identities of customers. You are currently passing in the following tabular features into a model in order to predict whether a given customer is lying about their identity: `income`, `phone_local`, `phone_confirmed`, `email_confirmed` and `verified_income`.

Consider these two sample training observations:

customer	income	phone_confirmed	phone_local	email_confirmed	verified_income
John	80,923	False	True	False	False
Jane	90,413	True	True	True	True

At first glance, the use of tabular machine learning is completely reasonable. A GBM will make quick work of such tabular data, likely providing the best results if you have enough labeled training observations and you manage your hyperparameters. However, real production data does not actually look like this;. This tabular feature representation is one of convenience. It is an abstract “view” that has been created in order to train a tabular model. The data, in its original form, might instead look like so:

customer	timestamp	event
John	`01-01-2024 03:04:50`	`CreateAccountEvent()`
John	`01-01-2024 03:05:43`	`AddPhoneEvent(phone='1236540987', is_local=True)`
John	`01-01-2024 03:07:12`	`AddEmailEvent(email='john@gmail.com')`
Jane	`01-01-2024 15:42:51`	`CreateAccountEvent()`
John	`01-02-2024 07:43:49`	`AddIncomeEvent(income=80923)`
Jane	`01-02-2024 07:44:25`	`AddEmailEvent(email='jame@hotmail.co')`
Jane	`01-02-2024 07:45:41`	`AddPhoneEvent(phone='4217838914', is_local=True)`
Jane	`01-02-2024 07:48:53`	`ConfirmPhoneEvent(phone='4217838914', is_local=True)`
Jane	`01-02-2024 07:51:55`	`AddIncomeEvent(income=90413)`
Jane	`01-02-2024 08:05:03`	`ConfirmIncomeEvent(income=90413)`
Jane	`01-03-2024 11:18:29`	`FailedEmailAttemptEvent(email='jame@hotmail.co')`
Jane	`01-03-2024 16:33:49`	`AddEmailEvent(email='jane@hotmail.com')`
Jane	`01-03-2024 16:35:12`	`ConfirmEmailEvent(email='jane@hotmail.com')`

This is the complete history of every event observed of each customer. This construct is not really tabular. It is actually something more universal: a "ledger" of events. Each event streams in asynchronously. Each event is immutable such that once a customer does something, it stays on their ledger. Each event can contain any number of complex fields, and each field can have any data type (categorical, text, numeric, boolean, timestamp, geospatial coordinates, etc). Additionally, each event has an associated timestamp for when it was received. This data architecture pattern is called "Event Sourcing". It is extremely powerful for encoding business logic and maintaining a record of every customer's history for the sake of reproducibility. It defines the complete history of everything ever done by every customer in its full detail.

Here are the distinct attributes for each event in the example above:
- `event_type`: what the customer did (`CreateAccountEvent`, `AddPhoneEvent`, `AddEmailEvent`, etc)
- `phone`: The customers provided phone number
- `is_local`: Whether the phone number is local to the customer's reported address
- `email`: The customers provided email address
- `income`: The customers provided income
- `timestamp`: The time at which the event occurred

The ledger is the source of truth for everything that has ever happened, and will always contain a superset of the information available within any tabular view made from it.

You may be thinking that the ledger is more complicated to model than the tabular view we were looked at before. It certainly is more complicated, yes, however it contains significantly more information. For example, we can see that Jane originally misspelled her email address as `jame@hotmail.co`, so she couldn't verify it until she corrected it to `jane@hotmail.com`. We can see the duration of time that incurred between each event observed of a customer. All of this information *could be* vital to modeling an identity verification problem. Tabular machine learning is incapable of modeling all of these potential signals without significant manual preprocessing and feature engineering, all of which is subject to human bias and human error.

By modeling the data exactly how it already exists in its production source table, as opposed to using a manually constructed view, we may be able to skip all of the feature engineering! Feature engineering is the bane of tabular modeling. It is time-consuming, tedious, prone to error, and extremely hard to scale for real-time computation. It requires extensive testing, maintenance, and monitoring. Being able to use the *raw* data to model our problem instead of an arbitrarily unique abstract view of it allows us to instantly unburden the modeling process from all of these significant costs.

With the use of deep learning, we may create a representation of each customer at any point in time given all of the events that they have posted. We assume, from the perspective of our model, a customer's representation is defined by the sum of their interactions with us. This customer representation may then be used to solve any arbitrary machine learning problem with a single generalized modeling approach that does not require any manual feature engineering. This would allow us to focus exclusively on the construction of an automated modeling pipeline.

In summary, instead of creating tabular features from our raw transactional data to train a tabular model, we should instead attempt to model our raw transactional data as it already exists. In other words, instead of changing our data to fit our model, we should change our model to fit our data. This has many parallels to the history of machine learning for universal modalities. The modality of computer vision comes to mind. Before the birth of CNNs, data scientists were instead manually defining convolution kernels. This is, in essence, how we are currently modeling business problems: with manually hardcoded tabular features.

Example Use Cases

The above example may seem a little cherry-picked. I would like to provide a few more problem statements to highlight just how prevalent this data structure is:

1. Given every previous ride observed by an Uber customer, what is the probability that they will be late for the next ride?
2. Given every activity log observed by a customer's Apple Watch, what is the probability that they will meet their workout goal this week?
3. Given every single transaction posted by a credit card holder of Chase, what is their survival curve (either due to attrition or default) over the next five years?
4. Given previous energy usage events observed by a customer of Duke Energy, what is their expected energy usage for the next week?
5. Given the previous purchases observed by a vendor on Ebay, what is the probability that they will be reported as a "scammer" in the next week?
6. Given the previous transactions posted by a user of Venmo, what is the probability that the current transaction is an attempt to defraud another user?
7. Given the previous tweets posted by a user of Twitter, what is the probability that this user is a bot?

There are hundreds of more problem statements associated with dozens of varying industries. This framework that I am describing is applies to all of them.

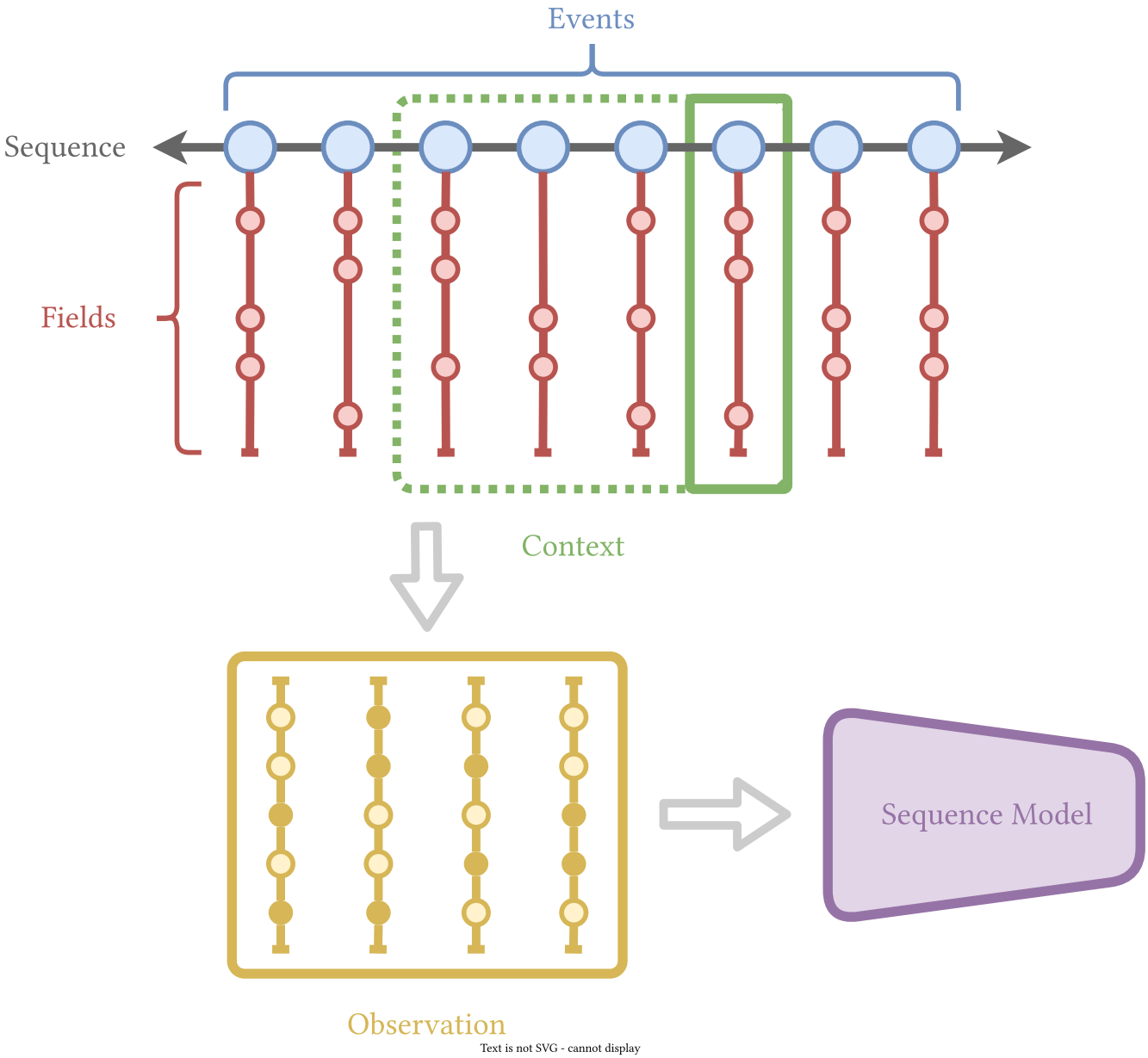
Terminology

It will be helpful to define some terminology before going forward. I will be discussing the architecture of an extensible ***sequence model***. The sequence model is able to train on ***observations***, which are a slice of a ***sequence***. A sequence is made of multiple ***events***, in which each event may have any number of ***fields***, which may have multiple possible data types. I may refer to this data as being "sequential", "transactional". It really is, however, a sequence of multivariate events with nullable, heterogeneous fields.

The population of sequences exists in some data table, in which each event is a record. I refer to this source of raw data as a ***ledger***. I want to go through the ledger, find all of the unique sequence IDs (IE, customer IDs), and find all of the events that exists within each sequence. Each event includes multiple fields. Every field exists as a column in this table.

I then want to stream over each sequence, looking at every event available within each sequence. I will then sample random events from the sequences. Each event has an equal probability of being sampled. After sampling each event, I then take the fields of that event, and then I collect the L (inclusively) preceding events' fields to calculate the ***context*** for the training sample. If there are not L preceding events before the sampled event, then the context is equal to however many events are available. I then pad and collate the context to create an ***observation***.

I then create many more observations from other sampled events, some of which may be from the same sequence, in order to create a training batch, which I then pass into the sequence encoder. Observations are used to pre-train and fine-tune the sequence model.



The model architecture, which I will discuss in detail in the next section, utilizes transformer-encoder blocks in a manner similar to BERT. The sequence model is creating a representation of the sequence given the context to answer questions about the sequence as a whole. This is in contrast to models like GPT, which utilize transformer-decoder blocks to predict subsequent events. The data structure that I have described above may seem similar to how a corpus is sampled to train a models like BERT. That is not entirely inaccurate. However, there is two significant differences:

1. You may think a list of tokens as being a single discrete field, whereas we need to support multiple fields of different data types. In other words, my model architecture requires one more dimension than BERT.
2. BERT samples observations at a sequence-level, but we need to sample observations from sequences at an event-level. For example, a customer with 10,000 events should result in approximately 10 times more observations than a customer with only 1,000 events. We are creating observations from the context, which are each defined by a randomly sampled event.

Here is an excellent video that better describes how BERT works, which is a prerequisite to understanding the model architecture described below.

Data Preprocessing for Efficient Streaming Operations

I found success in storing the data in a row-major format for custom streaming operations. `ndjson` and `avro` are both good options. I found that `parquet` had issues supporting complex, nested fields. I store my data in many small `avro` files, in which each sequence was stored as an object.

Within each sequence object, I stored the `sequence_id` (`str`), `event_id` (`list[str]`), event fields (`dict[str, list[int] | list[float] | list[str]]`), and event targets (`list[int] | list[float]`). With this format, I may simply sample any event index number, and then slice the context directly from the event fields (`slice(max(0, idx - L), index)`), which can be trivially padded and collated to an input tensor.

This data structure ensures that the grouping and filtering operations required to collect all of the events for each sequence will not bottleneck the model training process. In other words, it is way to optimize streaming larger-than-memory sequences from disk. As a reference to the `pytorch-lifestreams` python library, developed primarily by Dmitri Babaev, I refer to this data structure as a ***lifestream***.

As a sidenote, performance may be further improved by utilizing another data format, such as `protobuf`. I expect that `protobuf`, as an alternative to `avro`, would be approximately 30% faster to decode at a negligible cost (~10%) to the size of compressed files.

Tensor Notation

Given that we are talking about a rather complicated model structure, here is a reference to the common dimensions used for the tensors:

Tensor Notation	Hyperparameter Value Name	Definition
N	`batch_size`	Batch Size
L	`n_context`	Context Size of each observation
F	`n_fields`	Number of Fields
C	`d_field`	Hidden Dimension for each Field
$F * C$	`d_field * n_fields`	Hidden Dimension for each Event

Background

TabBERT

In early 2021, IBM published *Tabular Transformers for Modeling Multivariate Time Series* (ICASSP, 2021) in which they described a novel model architecture (TabBERT) that could outperform GBMs trained on such handcrafted tabular features for a set of supervised problems with sequential data.

In essence, they are framing the sequence as a two dimensional array. One dimension of the array represents each event in the sequence, and the second dimension represents each field in each event. Each null field gets replace with a null token `[NULL]`, and sampled observations that are shorter than the maximum sequence length get padded with events full of padding tokens `[PAD]`. In their implementation, every single field is limited to being exclusively discrete, such that each value is an integer that needs to be embedded via a standard embeddings table with respect to each field.

BERT was embedding a 1D discrete input of tokens (a sentence of words) into 2D space (an array of embeddings):

```
def embed(tokens: Int[torch.Tensor, "N L"]) -> Float[torch.Tensor, "N L C"]:
    ...
```

Whereas TabBERT embeds a 2D discrete input (a sliced sequence of events) into 3D space:

```
def embed(tokens: `Int[torch.Tensor, "N L F"]`) -> Float[torch.Tensor, "N L F C"]:
    ...
```

TabBERT then utilizes a hierarchical transformer-encoder architecture with two encoders. The first encoder (in my terminology, the ***field encoder***) lets every field embedding attend to every field embedding within an event. Those attended field representations are then concatenated to represent the event as a whole (`["N L F*C"]`). The second encoder (in my terminology, the ***event encoder***) lets every event representation to attend to one another. The sequence encoder is constructed similarly to BERT, such that there is an appended class token that may be used to represent the sequence as a whole, but one can also use the attended event representations for a MLM-like self-supervised learning task for model pre-training. They defined a custom pre-training task in which a

portion of the events and fields are masked, and the event representations outputted from the sequence encoder needs to be able to reconstruct the masked events and fields. For fine-tuning, the appended class token is passing through a MLP to solve the supervised task at hand.

For those unfamiliar with hierarchical transformer architecture, a great analogy comes from the domain of computer vision. If one is building a representation of an image, ideally each pixel should interact with every other pixel. However, if one is building a representation of a video, it would be virtually impossible to allow every pixel of every frame to interact with every pixel of every frame. Instead, it is common to first build a representation of each frame by letting each of its pixels interact with one another, and then build a representation of the video by allowing each representation of each frame interact with every other representation of each frame. Similarly, TabBERT breaks down a very large and complex problem into two smaller problems: representing each unique event and then using those event representations to create a representation of the sequence.

TabBERT, while elegant, did come with some major drawbacks. The largest of which is that their implementation required that every field be coerced into a categorical data type. For example, dollar amounts could not be fully represented, but you can bin them into categorical levels:

Continuous Input	Discrete Output
$4.95	`"$x<$5"`
$8.50	`"$5<x<$10"`
$19.95	`"$10<x<$20"`
$103.32	`"$100<x<$200"`

Coercing every field to become of a categorical data type is not only a manual task, but it comes with model performance costs. Much of GBM's success comes from their ability to define arbitrary cutoff points for continuous features. For example, in some fraud patterns, fraudsters might prefer gift cards, which commonly come in denominations of exactly $25, $50, or $100. In such a fraud pattern, transactions with dollar amounts equal to exactly those values may be far more likely to associated with known fraud patterns than transactions with dollar amounts with, say, values around $25.08, $49.12, or $99.53. For some tasks, arbitrary precision of continuous fields *might* be extremely important such that binning the continuous fields to become discrete destroys valuable information.

Additionally, the pre-training task suffers from the masked categorical targets. It is not aware of the ordinal nature of the binned categories. For example, if a masked dollar amount is actually $9.95 but the model predicts that the value is in the bucket `"$10<x<$20"`, the loss function harshly penalizes the model even though the model was almost correct. By "harshly", I mean that the loss function believes that the models prediction of `"$10<x<$20"` is as wrong as a prediction of `"$100<x<$200"` would have been.

UniTTab

In 2023, a small Italian consulting firm Prometeia published *One Transformer for All Time Series: Representing and Training with Time-Dependent Heterogeneous Tabular Data*, which introduced the UniTTab architecture. UniTTab made use of some very interesting ideas to represent continuous field values. Their novelties included the use of Fourier feature encodings to "embed" floating point field values with great precision. They referenced the NeRF (Neural Radiance Fields) paper which highlighted how Fourier feature encodings provide neural networks with a better representation of floating point values than passing in raw scalar values.

Fourier feature encodings effectively embed the true value of continuous inputs. They are quite similar to the sinusoidal positional embeddings used by early original transformer-based models. Here is a nice video that illustrates how this technique works.

UniTTab also adapted TabBERT's custom self-supervised learning task to work with continuous fields. Instead of trying to reconstruct the raw scalar values of each field via regression, UniTTab simplified to problem to become one of ordinal classification, in which the model attempts to determine the discrete quantile bin of masked

continuous field values. They modified the loss function to "smoothen" the loss if the predicted binned logits are closer to the actual binned target value, a technique that they described as "neighborhood loss smoothing".

UniTTab's improvements over TabBERT resulted in significantly better performance. UniTTab did not share its source code, however. Additionally, they were quite vague in the implementation. They require that each event be associated with a registered "row type", and that each "row type" has a required, non-nullable schema, which is a significant limitation. I designed a modified approximation of UniTTab, and I found that it outperformed my implementation of TabBERT (both of which outperformed GBMs!)

FATA-Trans

In November of 2023, Visa published the FATA-Trans paper. FATA-Trans was built on top of TabBERT, and supported only discrete fields and non-nullable timestamps. They included two major contributions: the ability to encode timestamps, and the ability to use tabular features alongside sequential data. Theoretically, one could already pass in tabular features by making the values homogenous among every event in the sequence, but as Visa stated, this is pretty computationally inefficient. They concluded that their architecture had marginal improvements over TabBERT.

Consolidating Sequence Modeling with Modular Fields

TabBERT, UniTTab, and FATA-Trans have all contributed a great deal to sequential modeling. TabBERT introduced the idea of hierarchical attention to capture the two-dimension nature of multivariate sequences. UniTTab improved upon TabBERT to utilize continuous fields. FATA-Trans introduced encoding timestamps and tabular features.

In this next section, I will be discussing a novel approach that I have developed to consolidate the embedding strategies of the previous papers with a focus on performance and extensibility:

1. Combines the abilities of the three aforementioned papers (supporting discrete, continuous, and temporal field types), while also simplifying the architectural rigidity of UniTTab.
2. Introduce ideas that I believe will be able to represent "entities", geospatial coordinates, timestamps and dates. I am defining an "entity" as a categorical input with infinitely many, or effectively infinitely many levels. For example, a device ID, a login session, a phone number, or a merchant name.
3. Introduce the idea of including "embedded media", such as text, images, video, and audio within the context.

Because of the variety of these different types of fields, I have created a custom Torch module that will accept a list of field types. The module will instantiate submodules that will embed each of the unique fields. I have called this module the "Modular Field Embedding System" (MFES).

Modular Field Embedding System (MFES)

As stated above, UniTTab supports discrete and continuous fields through a system the authors call "row types", in which each event must have a specific type with a rigid, non-nullable structure. I have found this system to be inflexible, and not necessarily intuitive to implement either. instead offer an alternative system inspired by their approach that is more flexible. I refer to this system as the Modular Field Embedding System (MFES). MFES has been designed with extensibility in mind to support any field type.

In other words, instead of creating "row types" in the style of UniTTab, I am creating "field types". Each field will be able to fully represent the original field value, as well as the "non-valued" states (masked, padded, or otherwise null) where necessary. Each field type is completely modular in that its contents are defined within a nested TensorDict (basically a recursive dictionary of tensors). Each field type requires only three things:

1. A type-specific field embedding module (to create the field embeddings for a specific field type)
2. A (optional) type-specific field decoder (to turn an contextualized event representation back into field-level predictions for the self-supervised learning task). If one isn't specified, the field types will not be used in the self-supervised learning task.
3. A (optional) custom attention mask generation function to facilitate sparse attention.

In order to embed each field, we need to ensure that each field is able to be fully represented regardless of its state. There are four unique possibilities for any given field:

1. There is a field value is present (the field is "valued").

2. There is not a field value present because the field's event was padded (the field is padded)
3. There is not a field value present because there wasn't a field value available in the data source (the field is null) 4. There may or may not be a field value present, but the model is not allowed to see it (the field is masked)

Discrete Field Embeddings

As an extremely simple example, let's start with a simple model architecture that needs to support four discrete fields per event: `is_foreign`, `is_online`, `merchant_category`, and `transaction_type`.

I use torch's `TensorDict` and `tensorclass` implementations to bundle the heterogeneous fields. For those unfamiliar with these constructs, they are almost exactly how they sound. A `TensorDict` is a torch dictionary that can contain instances of `torch.Tensor`. A `tensorclass` may be used similarly to `dataclass`. I use it to create a unique, type-checked container for each field type.

Below is an example of the input to a sequence model with four discrete fields. The input for each discrete field is contained within a `tensorclass` called `DiscreteField`.

```
@tensorclass
class DiscreteField:
    lookup: Int[torch.Tensor, "N L"]

# example input with a batch size of 2, sequence length of 8, and 4 discrete fields
TensorDict({
    is_foreign: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    is_online: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    merchant_category: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    transaction_type: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
})
```

This may seem unnecessarily complex at first, but it is quite necessary to support multiple the contents of varying field types. Additionally, methods may be attached to each `tensorclass` to support field-type specific operations, such as masking, preprocessing, and how to define the targets for the self-supervised learning task.

The modular field embedding system for this field schema looks like so:

```
ModularFieldEmbeddingSystem(
    (embedders): ModuleDict(
        (transaction_type): DiscreteFieldEmbedder(
            # six unique transaction types plus padded, null or masked
            (embeddings): Embedding(9, 12)
        ),
        (merchant_category): DiscreteFieldEmbedder(
            # twenty unique transaction types plus padded, null or masked
            (embeddings): Embedding(23, 12)
        ),
        (is_foreign): DiscreteFieldEmbedder(
            # yes, no, padded, null, or masked
            (embeddings): Embedding(5, 12)
        ),
        (is_online): DiscreteFieldEmbedder(
            # yes, no, padded, null, or masked
            (embeddings): Embedding(5, 12)
        ),
    )
)
```

Each modular field embedder is accessible by the name of the field.

Upon passing in the above `TensorDict` into the `ModularFieldEmbeddingSystem`, the MFES will iterate over each of the four fields, embedding each of them by querying each field's `DiscreteFieldEmbedder` into four tensors of dimensionality `["N L C"]`. After embedding each discrete field, `ModularFieldEmbeddingSystem` will then

concatenate the embeddings into a single tensor of dimensionality `["N L F C"]`, which is then passed into the field encoder.

Representing the non-valued states (padded, null, or masked) is trivial in this case. They are simply additional tokens available within the `DiscreteFieldEmbedder`'s embedding table. This is almost exactly like language models, except in this case each unique field embedding module has its own embeddings for these non-valued states.

Continuous Field Embeddings

UniTTab's approach avoids the complications of having to represent null, padded, or masked continuous field values enforcing a rigid structure upon each "row type". I found this to be extremely challenging to implement. Instead, my approach fully represents continuous fields in their true form as, effectively, `enum` data types:

```
enum ContinuousFieldValue {
    Value(f32),
    Null,
    Padded,
    Masked,
}
```

In other words, a continuous field value can either contain a real number, or it could be non-valued, in which case it must be null, padded, or masked. I represent continuous fields with two tensors: `values` and `lookup`, both of dimensionality `["N L"]`.

The `values` tensor contains the floating point CDFs of the original values. The domain of values is inclusively between `0.0` and `1.0`. Wherever a field is non-valued (either null, padded, or masked), I impute `values` to be equal to `0.0`.

The `lookup` tensor contains one of four integers to explain the state of each field: (`{'[VAL]': 0, '[NULL]': 1, '[PAD]': 2, '[MASK]': 3}`). Please note that the `'[VAL]'` token is defined as `0`.

```
@tensorclass
class ContinuousField:
    lookup: Int[torch.Tensor, "N L"]
    values: Float[torch.Tensor, "N L"]

# example input with a batch size of 2, sequence length of 8, and 2 continuous fields, 4
discrete fields
TensorDict({
    amount: ContinuousField(
        lookup=Tensor(torch.Size([2, 8]), torch.int64),
        values=Tensor(torch.Size([2, 8]), torch.float32),
    ),
    balance: ContinuousField(
        lookup=Tensor(torch.Size([2, 8]), torch.int64),
        values=Tensor(torch.Size([2, 8]), torch.float32),
    ),
    is_foreign: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    is_online: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    merchant_category: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    transaction_type: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
})
```

Similar to UniTTab and NeRF, I can embed the `values` tensor with Fourier feature encodings. This process looks like the following:

$$B = (-8, 1)$$

$$\gamma(v) = [\cos(\pi B v), \sin(\pi B v)]$$

$$\text{FourierEncoding}(v) = \text{MLP}(\gamma(v))$$

In other words, I am embedding the continuous fields by multiplying `values` with a sequence of bands, `B`, defined as `range(-8, 1)` and then multiplying that again with `pi`. I then compute both `sin(values * B * pi)` and `cos(values * B * pi)`, concatenating these two sequences together to create `gamma`. This tensor is then passed through a simple MLP to represent the `values` to the neural network.

However, there is a small problem. Because I imputed the non-valued fields to `0.0`, how is the model able to differentiate a value that is masked, padded, null, or is actually a value but just happens to be equal to `0.0`? The solution is surprisingly simple. I can simply embed the `lookup` tensor with standard linear embeddings. Because of some mathematical wizardry, I am able to add these two embeddings to fully represent each and every continuous field value, whether they are valued, null, padded, or masked!

This is due to several wonderful happenstances:
1. When `values` is equal to zero, $\gamma(v)$ will result in alternating ones and zeroes, so that $\text{MLP}(\gamma(v)))$ will result in a very simple FourierEncoding for these special values
2. The three learned non-valued indicator embeddings (`[NULL]`, `[PAD]`, and `[MASK]`) will learn around the simple FourierEncoding in the same way that the embeddings of BERT or GPT was able to learn around the sinusoidal positional embeddings.
3. My field's non-valued states are all effectively mutually exclusive (a field value can not be both padded and null at the same time), and while a field can be both masked and null, the model should only ever see that it is masked.

While this may seem a little chaotic, it actually comes with a very beautiful runtime assertion to rigorously validate the two tensors `values` and `lookup` for each continuous field. - We know that every non-valued input should be imputed to `0.0` - We know that the `[VAL]` token itself is equal to `0`.

Therefore, we can *guarantee* that the element-wise product of `lookup` and `values` will always equal zero!

```
assert torch.all(values.mul(lookup).eq(0.0)) ,\
    "all values should be imputed to 0.0 if not null, padded, or masked"

assert torch.all(values.le(1.0)) ,\
    "values should be less than or equal to 1.0"

assert torch.all(values.ge(0.0)) ,\
    "values should be greater than or equal to 0.0"
```

One last caveat to this approach is related to the precision of the floating point tensors. Fourier feature encodings have a limited range (my implementation can only represent `[0.0, 1.0]`). Therefore, it is required to standardize the distributions of the continuous field inputs before passing them into the model. Thankfully, it is actually pretty easy to do with the right approach.

As I had mentioned above, UniTTab requires an ordinal classification pre-training task. In other words, we will need to classify which quantile bucket a masked value would fall into. If we chose a total of 10 quantile buckets (deciles) than we would need to determine to which decile the masked value belongs. The choice of quantile buckets is a pre-training hyperparameter itself (`n_quantiles`), so it is much better to calculate the CDF of the original values for the pre-training task, and then when we choose a value for `n_quantiles` we can simply calculate the appropriate bucket index by calculate `floor(n_quantiles * cdf)`. That means that we can use the CDFs for both the inputs of the model, and then modify the CDFs for for the targets too!

In practice, Ted Dunning's TDigest algorithm is able to calculate the CDFs of the original values as a *streaming* operation during both training and inference, which means we never have to calculate the CDFs as a batch operation. This is really important, especially at the scale of billions to trillions of data points, because otherwise the calculation of the CDFs would require a great deal of compute. This also saves a great deal of storage as well, because we do not have to store the original values, the normalized values, and also the binned values. We only have to store the original values!

There are potential alternatives to this strategy with which I have not yet experimented. Instead of embedding `values` with Fourier encodings and then embedding `lookup` with `torch.nn.Embedding` before adding those two embeddings together, we could instead aggregate them together before embedding once. This may be

accomplished by subtracting the `lookup` tensor from the `values` tensor, and passing in the resulting tensor into FourierEncoding. The model will learn that the negative integers `-1`, `-2`, and `-3` are each of a special representation, and that the floating point inputs in the range of $(0, 1)$ are of real values. You will need to expand the bands to $B = (-8, 3)$ to account for the larger domain.

Regardless, the `ModulerFieldEmbeddingSystem` is able to utilize instances of `ContinuousFieldEmbedder` for each of the continuous fields, each of which is dedicated to embedding an inputted `ContinuousField`.

```
ModularFieldEmbeddingSystem(
    (embedders): ModuleDict(
        (amount): ContinuousFieldEmbedder(
            (linear): Linear(in_features=16, out_features=12, bias=True)
            # masked, null, padded, or valued
            (positional): Embedding(4, 12)
        ),
        (balance): ContinuousFieldEmbedder(
            (linear): Linear(in_features=16, out_features=12, bias=True)
            # masked, null, padded, or valued
            (positional): Embedding(4, 12)
        ),
        (transaction_type): DiscreteFieldEmbedder(
            # six unique transaction types plus padded, null or masked
            (embeddings): Embedding(9, 12)
        ),
        (merchant_category): DiscreteFieldEmbedder(
            # twenty unique merchant categories plus, null padded or masked
            (embeddings): Embedding(23, 12)
        ),
        (is_foreign): DiscreteFieldEmbedder(
            # yes, no, padded, null or masked
            (embeddings): Embedding(5, 12)
        ),
        (is_online): DiscreteFieldEmbedder(
            # yes, no, padded, null or masked
            (embeddings): Embedding(5, 12)
        ),
    )
)
```

Similarly to the instance of `ModularFieldEmbeddingSystem` with only discrete fields, this `ModularFieldEmbeddingSystem` with heterogeneous field types will iterate over each of the six fields, embedding them individually and then concatenating their embeddings to create a single embedding for the entire batch of dimensionality `["N L F C"]`.

Temporal Field Embeddings

Working with dates and timestamps might seem tricky, but we can actually tackle it similarly to how we handled continuous fields! Temporal fields (dates / timestamps) may be processed as raw numerical data via UNIX Epoch time, the number of seconds or milliseconds since 1970. That numerical data is then passed through a `TDigest` to retrieve the CDF of the timestamp. The CDF is then passed through an instance of `TimestampFieldEmbedder` to create a timestamp embedding. The `TDigest` model ensures that outlier date / timestamp values are still usable.

```
@tensorclass
class TemporalField:
    lookup: Int[torch.Tensor, "N L"]
    values: Float[torch.Tensor, "N L"]

# example input with a batch size of 2, sequence length of 8
# 1 temporal field, 2 continuous fields, 4 discrete fields
TensorDict({
    timestamp: TemporalField(
```

```
        lookup=Tensor(torch.Size([2, 8]), torch.int64),
        values=Tensor(torch.Size([2, 8]), torch.float32),
    ),
    amount: ContinuousField(
        lookup=Tensor(torch.Size([2, 8]), torch.int64),
        values=Tensor(torch.Size([2, 8]), torch.float32),
    ),
    balance: ContinuousField(
        lookup=Tensor(torch.Size([2, 8]), torch.int64),
        values=Tensor(torch.Size([2, 8]), torch.float32),
    ),
    is_foreign: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    is_online: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    merchant_category: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
    transaction_type: DiscreteField(lookup=Tensor(torch.Size([2, 8]), torch.int64)),
})
```

In addition to passing in the raw timestamp data, you might instead include data related to the time difference since the previous event (duration), the number of seconds passed since the previous event. This could prevent the model from overfitting on irregular activity that is limited a small window of time. However, timestamps may still be important depending on your data. For example, the "Event Sourcing" pattern is not backwards compatible should your API schema change, such that some event types may not have been available in the past. It may be important for your use case to be able to explicitly tell the model about the absolute time an event took place may understand the API schema version at the time of any given event in order to prevent ambiguity.

Geospatial Field Embeddings

Geospatial data also seems rather tricky. However, we can one again use a technique similar to the continuous field embedding mechanism to accomplish this. Unlike the continuous or temporal fields, geospatial coordinates are defined by two numbers: longitude and latitude. Both longitude and latitude requires their own `TDigest` model.

```
@tensorclass
class GeospatialField:
    lookup: Int[torch.Tensor, "N L"]
    longitude: Float[torch.Tensor, "N L"]
    latitude: Float[torch.Tensor, "N L"]

# example input with a batch size of 3, sequence length of 64
# 1 geospatial field, 1 temporal field, 2 continuous fields, 4 discrete fields
TensorDict({
    location: GeospatialField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        longitude=Tensor(torch.Size([3, 64]), torch.float32),
        latitude=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    timestamp: TemporalField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        values=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    amount: ContinuousField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        values=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    balance: ContinuousField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        values=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    is_foreign: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
    is_online: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
    merchant_category: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
```

```
    transaction_type: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
})
```

However, using raw geospatial coordinates is not always the best course of action. If your data is too small it may lead to overfitting. If you are trying to create representations of ride-share drivers based on their previous trips, you might include both the pickup and dropout geospatial coordinate for each trip. Alternative, you could simply include the distance and zip code of the trip.

Additionally, the lines of longitude overflow at the prime meridian. This means that a coordinate with a longitude value of 179 is as close to the prime meridian as a coordinate value of –179. This is fundamentally different from how a number system works, and so it requires a slightly different strategy to decode during the self-supervised learning task (described below)

Entity Field Embeddings

Entities are extremely common in production datasets. By an entity, I am referring to one discrete item in an infinitely large set of items. The set of items, while similar to categorical data, is so large or otherwise ephemeral that each unique level in the category cannot possibly be explained by a unique embedding.

For example, whenever a customer logs into their account, I could create an ephemeral login session token that is unique. This login session identifier is stored an entity among all of the events that happen during the login session. The model could then use this login session ID to see which events happened during each login session.

Additionally, we might also consider each unique "merchant" as an entity. We might want to be able to allow the model to see which purchases happened at each merchant. This is different than "merchant name", which may include a rigorously cleaned string like `"mcdonalds"`. A "merchant" may instead include the address or store number, allowing even for a greater level of granularity.

Lastly, we might consider the devices of each customer to be entities. Device identifiers may be tracked and stored across multiple events observed of each customer. These device identifiers may allow the model to understand which event happened from which of the customer's devices, providing significant value for protecting customers from being hacked.

Needless to say, effectively tracking the locations, devices and login sessions of customers may be considered a breach of privacy. However, in other cases, such as fraud detection, such data points are absolutely critical for optimal coverage in order to deliver the best customer experience given customers' consent.

The use of entities is very common in recommendation systems, which typically create large lookup tables which are indexed with multiple lookup values created by many different hash functions in order to prevent hash collisions However, there are other ways of accomplishing the same goal.

Instead of using hashed embeddings in order to unique represent every possible entity, we could instead elect to simply try to differentiate between the entities available within an observation's context. In other words, we don't necessarily need to know which device you are currently using, but we just need to know whether that device is the same that you used yesterday. This can actually be done by assigning each unique device in the context window a single random number. We can guarantee that there will be, at most, the same number of unique devices equal to the size of the context window. The random lookup value assignment can change between each observation in order to prevent overfitting, but the assignment operation can be fixed to a seed value during inference for reproducibility.

```
@tensorclass
class EntityField:
    lookup: Int[torch.Tensor, "N L"]

# example input with a batch size of 3, sequence length of 64
# 1 entity field, 1 geospatial field, 1 temporal field, 2 continuous fields, 4 discrete fields
TensorDict({
    device: EntityField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
    location: GeospatialField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        longitude=Tensor(torch.Size([3, 64]), torch.float32),
```

```
        latitude=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    timestamp: TemporalField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        values=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    amount: ContinuousField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        values=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    balance: ContinuousField(
        lookup=Tensor(torch.Size([3, 64]), torch.int64),
        values=Tensor(torch.Size([3, 64]), torch.float32),
    ),
    is_foreign: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
    is_online: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
    merchant_category: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
    transaction_type: DiscreteField(lookup=Tensor(torch.Size([3, 64]), torch.int64)),
})
```

This technique is only possible because we are defining a context window with a upper-bound size limit. If we have context window with a maximum size of 64 then we know there are, at most, 67 maximum possible unique values that we need to represent (64 plus the three non-valued states). We are simply trying to differentiate these unique values from one another. Devices, login sessions, and merchants are ephemeral and infinite, and this novel mechanism allows us to represent them as such without storing many different large look up tables.

Media Fields

Using standard field types (discrete, continuous, temporal, geospatial, entity field types) solves a great deal of potential business problems. However, there are more advanced data types that may also be utilized, such as raw text, images, audio, and video. These are more complicated, and rely upon pre-trained models specific to each modality.

Textual Field Embeddings

We can also *potentially* use raw string text. This one is a little bit tricky, however. In effect, this is akin to running BERT inside of the modular field embedding system. As you can imagine, this can require extensive computational resources at scale. This happens primarily because the effective batch size for this inner-most BERT model becomes equal to `N*L*F`. In other words, you need to individually encode every single field of every event of every observation simultaneously.

For each event in each observation, we want to take the textual fields, tokenize their content, and then run them through BERT, collecting the text representation from the class token. There are two ways of doing this, neither of which are especially pleasant:

1. Use a single instance of a pre-trained BERT model and fine-tune it for all of the textual fields.
2. Use multiple instances of a smaller pre-trained BERT model and fine-tune them for each of the textual fields.

The BERT model would likely need to be limited to work with an extremely small token context in order to prevent running out of memory, hindering the quality of its field embeddings.

Additionally, pre-training textual field embedding modules is difficult! Running masked-language modeling *inside* the our custom self-supervised learning task is not possible. That being said, the BERT textual encoder itself is already pre-trained. At this current point in time, I do not plan on including a custom textual field event decoder to facilitate the self-supervised learning task. Instead, they will be frozen during pre-training, and then unfrozen during fine-tuning.

Images, Audio & Video

In addition to working with just embedded textual fields, one could *theoretically* include images, audio, and video data as well. In other words, any event of any sequence could include a reference to a file. As a streaming operation, that file is fetched, opened, preprocessed, and embedded.

For example, suppose you are trying to create representations of all Twitter users. Each Tweet may include a photo or video, so that each Tweet event may optionally include a photo or video. In other words, each `TweetEvent` might include the following fields: `timestamp`, `content`, `device`, `location`, `photo`, `video`, `is_deleted`. The photo (or video) is then embedded, as are all of the other fields. Additionally, each Twitter user may include post a `ProfilePictureUpdateEvent` may include the following fields: `timestamp`, `device`, `location`, `video`.

This will certainly add bottlenecks to the data streaming pipeline, there are some ways to optimize it. For example, you could store each sequence's ledger as its own file, and then store all of its associated media in separate files. All of these files for each sequence is compressed into a single `TAR` file, which could then be streamed through and sampled from.

The usage of media is extremely complicated, but really emphasizes the versatility of approaching your data with sequential modeling!

Putting it all together: MFES and examples

Discrete, continuous, temporal, geospatial, entities, media, and external fields. MFES is able to work with all of these field types over large sequences of data. That means I am able to input sequences that describe all of the transactions ever posted by a customer of a financial institution:

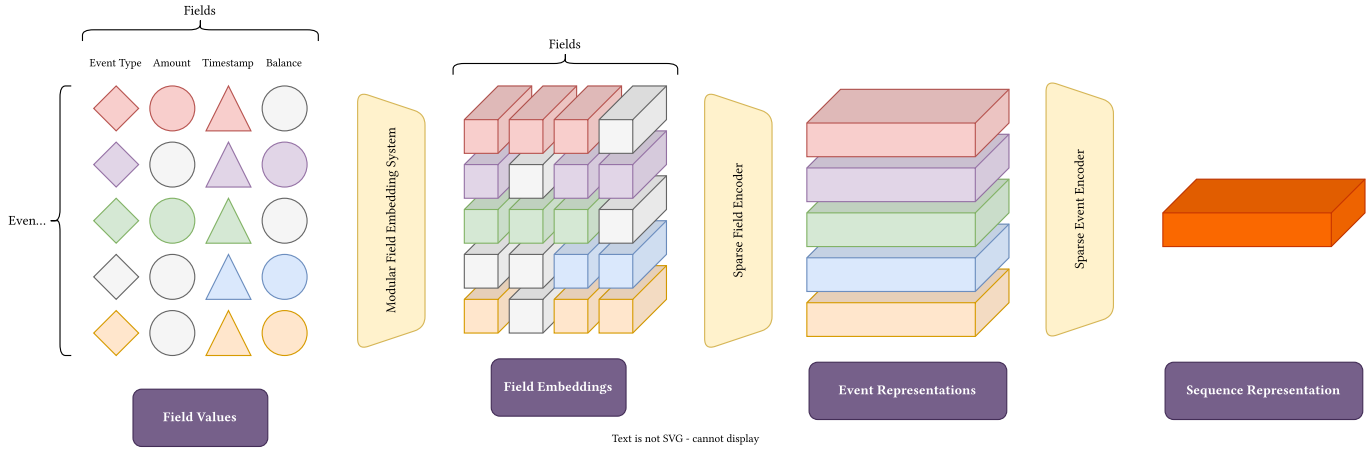
Device ID	Action	Amount	Location	Timestamp	Comments	Merchant Name
`e8e905fbb00f`	Annual Fee	395.00		2022-03-19 08:34:02	Annual Card Fee	BigBank
	Purchase	171.54	(-74.204573, −158.007852)	2022-03-21 11:19:53	Home improvement supplies	HomeCraft
	Purchase	464.69	(-76.638826, −36.341502)	2022-04-30 20:43:02	Charity donation	GiveBack
`e8e905fbb00f`	Online Payment	463.58		2022-09-13 16:21:23	Hotel booking	StayInn
`f2e31f29343b`	Dispute Transaction	489.35	(-34.316692, 170.608224)	2023-05-01 20:40:15	Pet supplies	PetWorld
`e8e905fbb00f`	Refund	53.73		2023-06-09 06:55:00	Refund for returned item	ReturnDesk
`e8e905fbb00f`	Balance Inquiry			2023-08-23 01:48:57		BigBank
	Purchase	25.00	(81.202198, 175.041279)	2023-11-18 19:42:07	Coffee shop	BrewBeans
	Purchase	251.61	(-41.539246, 154.148774)	2023-12-01 22:12:23	Transfer to friend	PeerPay
`e8e905fbb00f`	Balance Inquiry			2024-02-11 09:38:10		BigBank

This approach is extremely versatile. It is able to work with any data type. Additionally, it is able to work with your data exactly how it already is. Similar to language and vision, there is effectively zero preprocessing. There are no concerns about non-valued fields.

Model Architecture Summary

Upon the creation of the field embeddings with the Modular Field Embedding System, TabBERT's hierarchical transformer-encoder architecture is able to build sequence and event representations as before. I include two

transformer-encoder modules, the “field encoder” and the “event encoder”. The field encoder allows each field to interact with every other field within each event. The contextualized field representations are then concatenated to form an event representation. Each event representation then interacts with every other event in the event encoder, which produces contextualized event representations, as well as a sequence representation via a special `[CLS]` token, which is appended to the inputted event representations. The event representations are used to pre-train the model, and the sequence representation can be used for arbitrary fine-tuning tasks.



Self-Supervised Learning Strategy

One of the many advantages of this network architecture is the opportunity to utilize self-supervised learning (SSL). In many business problems, there is a large amount of unlabeled data that traditional machine learning models are not able to utilize. The modality of language has benefitted enormously by applying masked language modeling (MLM) to pretrain models like BERT. TabBERT, as the name implies, also utilized an adaption of MLM, in which they mask random fields or events.

Masked Event and Masked Field Modeling Tasks

Applying SSL to our data is tricky, however, because every field can be of a different type. We needed to ensure that each field type is able to support non-valued states so that we are able to mask any field. In addition to being able to mask any field, we also need to be able to decode the contextualized event representations back into their original values. This is very easy for a discrete field, however it is more difficult for the other fields.

Device ID	Action	Amount	Location	Timestamp	Comments	Merchant Name
`e8e905fbb00f`	`[MASK]`	395.00		2022-03-19 08:34:02	Annual Card Fee	BigBank
	Purchase	171.54	(-74.204573, −158.007852)	2022-03-21 11:19:53	`[MASK]`	HomeCraft
`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`
`e8e905fbb00f`	Online Payment	463.58		2022-09-13 16:21:23	Hotel booking	StayInn
`[MASK]`	Dispute Transaction	489.35	(-34.316692, 170.608224)	2023-05-01 20:40:15	Pet supplies	PetWorld
`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`
`e8e905fbb00f`	Balance Inquiry			2023-08-23 01:48:57		BigBank
`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`	`[MASK]`
	Purchase	251.61	(-41.539246, 154.148774)	`[MASK]`	Transfer to friend	PeerPay
`[MASK]`	Balance Inquiry		`[MASK]`	2024-02-11 09:38:10		BigBank

Semi-Ordinal Classification of Quantiles

For the continuous, temporal, and geospatial fields, instead of attempting to reconstruct the original CDFs, we can instead attempt to reconstruct the bin of the CDFs. This requires that we set a hyperparameter, `n_quantiles`, to define the number of bins for the customer SSL task. Going forward, let's assume we want to calculate the number of deciles (`n_quantiles = 10`).

If one of the masked continuous fields has a CDF of `0.05`, the model should learn to predict that this value belongs in the 0th decile. If another masked continuous field has a CDF of 0.51, the model should learn that this value belongs in the 5th decile. Generally speaking, every masked CDF should be mapped to the bin `floor(CDF * n_quantiles)`.

However, this alone has an issue. We are penalizing the model if it guesses the wrong bin, but we also want encourage the model if it guesses the incorrect bins that are *closer* to the correct bin. In other words, if the model says that the masked value belongs in the 8th decile, but in reality it belongs in the 9th decile, then it should punished less than if it had said the the masked value belongs in the 0th decile. In other words, we want to run a semi-ordinal classification task. We need to apply the "neighborhood loss smoothing" function from the UniTTab paper, however we need to modify it in order to support the non-valued states of null and padded as well.

Geospatial fields are a little more complicated, however, because lines of longitude wrap around at the prime meridian.

Fine-tuning Sequence Models

The fine-tuning of this sequence model is pretty straightforward, thankfully. The sequence representation is a tensor of fixed size. In my experience, a properly pre-trained sequence model can fine-tune in a matter of hours on modest hardware.

Versatility of Supervised Tasks

Sequence models are able to support a variety of tasks. In my implementation, I have designed my sequence model to support event-level supervised tasks: classification, regression, and survival. In other words, I can have different target labels depending on which event was sampled. This is in contrast to sequence-level tagging, which would restrict the target to be homogeneous for every event in a sequence. Additionally, I have enforced a

mechanism that I call “nullable tagging”, such that I can include null values in my targets. Events with null targets are able to be used in the historical context of future events, but they can not be sampled. I found this mechanism useful for solving the “clipping problem” which I describe in a later section

Observation Sampling Strategies
Sampling events from a sequence to create observations is difficult. Sampling too many overlapping observations from a sequence can quickly result in overfitting. By “overlapping observations”, I am referring to observations that share events with one another. I have developed an intuition that works well for me. I found success in iterating over each sequence in the population of sequences. Within each sequence, I will sample (`len(sequence) / n_context`) many events on average. In other words, I will independently sample random events from a sequence at a rate of (`1 / n_context`).

This is really unique to this problem. In computer vision, you can uniformly sample from the population of images. In language modeling, you can uniformly sample from the population of documents from a corpus. However, for sequence modeling, sampling observations at a sequence-level does not necessarily work because some sequences may have very few events. For example, you may be running a financial institution with 10 million customers, each with a credit card. However, a large portion of your credit card users may be “gamers” that only signed up for the card to collect a sign on bonus. These inactive customers may only tens of events on their records, whereas other customers may have thousands of events in their records.

Sampling uniformly from each customer’s sequence will result in sampling the same few transactions from your inactive customers a hundred times before you have sampled through the events of your active customers. This results in extraordinarily long training times and poor performance because your model is overfit on the less active customers and underfit on the more active customers.

Automated Model Training Pipeline
With the data preprocessing and model architecture, pre-training, and finetuning stages being clearly defined, there is a way to automate these stages from start to finish via workflow orchestration.

Workflow Orchestration
There are many wonderful workflow orchestration engines out there: Airflow, Kubeflow Pipelines (KFP), and Metaflow are the three most common python-based orchestration engines for data science applications. Airflow gives me nightmares. KFP doesn’t enable local development. Metaflow is the best of the big three orchestrators in my humble opinion, but its class-based SDK bothers me. I elected to instead use Flyte because of its beautiful SDK and pleasant community. Flyte’s SDK (FlyteKit) allows for extraordinarily elegant task definitions that are able to utilize local libraries. Additionally, I am able to seamlessly execute my workflows on my local machine for rapid prototyping and development.

In my training pipeline, there are six major steps that are required:
1. **Data Validation**: Parse the inputted ledger and confirm that the requested field types are available and valid
2. **Data Preprocessing**: Convert the inputted ledger to a lifestream for optimal streaming operations
3. **Creating TDigests**: Create TDigest models for each of the field types that require them, so that we can convert their field values to CDFs as a streaming operation
4. **Model Pre-Training**: Execute the self-supervised learning task to pre-train the model
5. **Model Fine-Tuning**: Execute the supervised learning task to fine-tune the model
6. **Model Inference**: Predict supervised target labels for ad-hoc analyses
7. **Model Compilation**: Export the model to a universal format

Pipeline Parameters
The pipeline executes as a function of the ledger dataset, as well as a large set of parameters that come with healthy default values.

#TODO add `Hyperparameters`

Peripheral Pipeline Steps

Because the orchestrated pipeline has been developed to operate automatically, we can actually incorporate a great deal of utility functions to execute within the pipeline.

1. Run a series of tests on the ledger to test the quality of the data
2. Generate visualizations for each of the input fields within the dataset
3. Automatically quantize the model for more efficient model inference
4. Compare model scores between trained torch model and the compiled model to validate model compilation
5. Attempt model rollout to production environment (canary deployment strategy)
6. Distill trained model into traditional tabular model (GBM) for interpretability
7. Generate report on model performance on out-of-sample data
8. Generate whitepaper on model hyperparameters, including information from aforementioned steps

Additional Considerations

Sequence Entropy

A unique characteristic of such multivariate sequences is that they are not nearly as structured as human language. Multivariate sequences can be quite noisy, whereas human language is bound by the rules of grammar. Human language has evolved to be structured, redundant, and fault-tolerant. For example, An adjective must always be followed by another adjective or the noun they describe. If you were to shuffle all of the words in a sentence, the fact that it was changed will be extraordinary obvious. However, if one were to just randomly mask out a random word, you may still have a very good guess as to the general message of the sentence regardless.

On the contrary, our complex sequences of data tend to have relatively less structure. If you shuffle all of the events in a sequence, it will likely remain just as "plausible" as before. However, if you were to mask out a random event, it will be much more difficult to reconstruct. For example, if you had to go both grocery shopping and also top your tank with gas, what portion of the time do you go to the grocery store *before* you go to the gas station? There is no right answer. The order is almost completely arbitrary.

Additionally, pre-training a large language model on every human language is extremely complicated due to large vocabulary sizes, disproportionate word usage, quotes, mannerisms, plagiarism, and writing styles. In my experience pre-training sequence models with transactional data is extremely simple in comparison because there is less structure to be learned. The hardware requirements are surprisingly minimal.

Arbitrary Dimensionality

In all of my examples above, I use a specific dimensionality: Each sequence contains events, and each event contains fields. In other words: `Customer > Transaction > Field`. This is extremely simple, and fits the vast majority of use cases that come to mind. However, I realize there are counter examples to this design.

Walmart may want to model their transactions differently. For example, they might want to include the concept of "shopping trips", in which each customer might make multiple shopping trips, and during each shopping trip they might purchase multiple items, and each item may have multiple fields.. So, instead of `Customer > Transaction > Field`, we might instead model the sequence as `Customer > Trip > Item > Field`.

While the implementation of the model will change completely, the concept is not all that different. The usage of sequential modeling is still applicable. I do not currently intend on developing this 3D implementation, however.

The Clipping Problem

I came across an interesting complication while training sequential models on slices of time series. It is intuitive in hindsight, but it is challenging to identify.

It is common to subset slices of time series based on some time window (IE: all events between January 2020 and January 2023). This can lead to very unexpected behavior, however, due to what I have called the "clipping problem".

Simply put, the model may sometimes not have enough information to understand if a sequence with an event in the onset of the window is truly the first event in the sequence, or if it just looks like the first event in the sequence because the prior events were filtered out. There is ambiguity in what had happened before the context.

This problem has multiple solutions:
1. Include a "buffer" window in the data, during when the model may sample the events as historical context, but not as the event at the end of an observation
2. Include information regarding the start of the sequence, such as the creation of the account (`AccountOpenEvent`) or a field that provides the time since the sequence started (`account_tenure`)
3. Instead of creating a fixed time window (Jan 2020 to Jan 2023) at an event level, perhaps filter your data to only accounts that were opened between some two dates (depending on your use case)

All three of these solutions prevents the ambiguity between an observation that includes an artificial cutoff versus an observation that includes the start of a sequence.

The Flushing Problem

A unique adversarial vulnerability arises when modeling sequential data with a fixed context size depending on the types of events allowed to fill the context window. Theoretically, an ill-intended individual could "flush" the context by spamming innocuous events. In other words, an attacker may simply "login" and "logout" of their account several thousand times in order to attempt to manipulate the model in some way.

A more concrete example: A savvy hacker, having recently hacked into their victim's account at Big Online Store, could choose to reset the user's password, email, phone number, and mailing address before attempting to purchase gift card codes. Such risky actions, which may otherwise result in a security alert, may go unnoticed if the fraudster intentionally spams many login events between each nefarious action, such that the model doesn't see more than one such nefarious action at any point in time. In other words, if you perform a thousand low-risk events between every high-risk event, the model will not see just how risky your recent actions truly are.

The risk of such an attack may be mitigated by multiple means:
1. Increase the context size.
2. Set up policies to flag high event rates, where needed.
3. Do not include trivial events (login / logout events) in the context, but rather represent them whenever possible, as entity fields (such as a "login session")

Including Tabular Data and Multiple Sequences of Varying Event Rates

I have not yet explored integrating static tabular data with my sequential data, although this approach has been explored by Visa Research in their FATA-Trans paper. I am similarly curious about working with multiple sequences of data per account, in which each sequence has different event rates. For example, one sequence of 48 monthly billing statements over the last four years, another sequence for the last 256 customer financial transactions, and a final sequence of the last 2048 online click stream events. This would allow the model to learn from multiple sources without low frequency events being excavated from the context by high frequency events.

The most significant obstacle to implementing multiple sequences of varying event rates is the systematic synchronization of these events as a streaming operation. For example, which monthly statements should be available to the context given which online click stream events? This would require each click stream event to contain an index to its corresponding monthly statement.

Regardless, the utilization of multiple sequences and tabular data is yet another solution to the aforementioned "flushing problem" because the signal may be captured from multiple potential sequences of varying event rates.

Sub-Quadratic Alternatives to Self-Attention

An interesting property of sequential data is that events asynchronously (they often arrive in separate streaming messages). Consequently, there is a potential optimization trick for real-time inference. Using emerging alternatives to transformers, such as RWKV or Mamba, one can actually save an enormous amounts of the compute requirements for inference. The memory complexity with respect to the context size decreases from quadratic to constant!

- Store sequence state representations in a in-memory cache like Redis
- Whenever a new event arrives:
  1. Let each field within an event attend to one another
  2. Concatenate the attended fields to create the new event representation

3. Retrieve the current sequence representation
4. Update the sequence representation with the new event representation
5. Pass the new sequence representation to a decision head to create and return a new model score
6. Save the new sequence state representation

Conclusion

#TODO add conclusion