

## Attendees

## Contents

**Present** Anssi\_Kostiainen, Belem\_Zhang,  
Chai\_Chaoweeraprasit, Dom,  
Eric\_Meyer, Feng\_Dai, Geun-Hyung,  
Geun-Hyung\_Kim, Judy\_Brewer,  
Junwei\_Fu, Ningxin\_Hu,  
Rachel\_Yager, Rafael\_Cintron,  
Takio\_Yamaoka, Wanming,  
Zoltan\_Kis

**Regrets** -

**Chair** Anssi

**Scribe** Anssi, anssik, dom

1. [Conformance testing of WebNN API](#)
  1. [Web Platform Tests](#)
2. [Ethical issues in using Machine Learning on the Web](#)

## Meeting minutes

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### Conformance testing of WebNN API

**Anssi:** interoperability testing helps ensure compatibility among existing and future implementations ... in the context of ML, reaching interop is not necessarily easy given the variety of underlying hardware

... Chai is involved in Microsoft DirectML and has experience in this space

*Slideset:* [https://lists.w3.org/Archives/Public/www-archive/2021Oct/att-0017/Conformance\\_Testing\\_of\\_Machine\\_Learning\\_API.pdf](https://lists.w3.org/Archives/Public/www-archive/2021Oct/att-0017/Conformance_Testing_of_Machine_Learning_API.pdf)  
[\[ Slide 1 \]](#)

**Chai:** conformance testing of ML APIs is quite important

[\[ Slide 2 \]](#)

**chai:** the problems can be categorized into 3 categories:

- ... the ML models need to run on a wide variety of specialized hardware
- ... my work with DirectML is at the lowest level before the hardware in the windows OS
- ... windows has a very broad scale of hardware
- ... esp with specialized accelerators
- ... they don't share the same architecture and have very different approach to computation
- ... ensuring the quality of results across this hardware is really important

... another issue is that most modern AI computation relies on floating point calculation  
... FP calculation with real numbers accumulate errors as you progress in the computation - that's a fact of life  
... there are trimming problems which create challenges in testing the results of ML API across hardware  
... this is a daily issue in my work testing Direct ML

### [\[ Slide 3 \]](#)

**Chai:** Karen Zack's Animals vs Food prompted a an actual AI challenge  
... humans don't have too much difficulty doing the difference, but while many models are able to perform, they tend to give results with some level of uncertainty  
... showing the importance of reliability across hardware

### [\[ Slide 4 \]](#)

**Chai:** when we run the results of ML models, there are 4 groups of variability  
... the most obvious one is precision differences - half vs double precision will give different results  
... most models run with single precision float, but many will run with half  
... Another bucket is hardware differences - even looking at CPU & GPUs, different chipset may have slightly different ways of computing and calculating FP operations  
... accelerators are often DSP based; some may rely on fixed point calculation, implying conversion, to very different type of formats (e.g. 12.12, 10.10)  
... A third source of variability is linked to algorithmic differences  
... there are different ways of implementing convolutions, leading to different results  
... Finally, there is numerical variability - even on the same hardware, running floating point calculation, there may be slight difference across runs  
... and that can be amplified by issues of lossy conversion between floating point to fixed point,  
... these issues compound one with another, so there is no guarantee of reproducible results

### [\[ Slide 5 \]](#)

**Chai:** how do we deal with that in testing?  
... Many test frameworks use fuzzy comparison that provides an upper boundary (called epsilon) to an acceptable margin of differences  
... the problem of that approach in ML is that it doesn't deal with the source of variabilities we identified  
... A better way of comparing floating point values is based on ULP, unit of least precision  
... the distance measured between consecutive floating point values  
... a comparison between the binary representation of different floating point values, applicable to any float point format  
... Using ULP comparison removes the uncertainty on numerical differences  
... it also mitigates the hardware varaibility in terms of architectural differences because it compares the representations

### [\[ Slide 6 \]](#)

**Chai:** this piece of code illustrates the ULP comparison  
... the compare function convert the floating point number into a bitwise value that is used to

calculate the difference and how much ULP that represents  
... e.g. here, only a difference of 1 ULP is deemed acceptable  
... We use ULP to test DirectML  
... the actual floating point values from the tests are never the same

[\[ Slide 7 \]](#)

**Chai:** to make the comparison, you need to define a point of reference, which we call the baseline  
... the baseline is determined by the best known result for the computation, the ideal result  
... this serves as a stable invariant  
... for directML, we have computed standard results on a well-defined CPU with double precision float  
... we use that as our ideal baseline  
... we then define the tolerance in terms of ULP - the acceptable difference between what is and what should be (the baseline)  
... the key ideas here are #1 use the baseline, #2 define tolerance in terms of ULP

[\[ Slide 8 \]](#)

**Chai:** the strategy of constructing tests can be summarized in 5 recommendations:  
... we recommend testing both the model and the kernels  
... each operator should be tested separately, and on top of that, a set of models that exercise the API and run the results of the whole model  
... for object classification models, you would want to compare the top K results (e.g. 99% Chiwawa, 75% muffin)  
... making sure e.g. the 3 top answers are similar  
... it's possible to have tests passing at the kernel level, but failing at the model level  
... 2nd point: define an ideal baseline and ULP-based tolerance  
... you might have to fine-tune the tolerance for different kernels  
... e.g. addition should have very low ULP, vs square root or convolution

**anssi:** thanks for the presentation  
... highlights how different from usual Web API testing is in the field  
... most likely similarities are with GPU and graphic APIs  
... We've had some early experimentation with bringing tests to WPT, the cross-browser platform testing project that is integrated with CI

**RafaelCintron:** any recommendation in terms of ULP tolerance? what does it depend on?

**Chai:** simple operations like addition, low tolerance (e.g. 1 ULP)  
... for complex operations, the tolerance needs to be higher  
... sometimes, the specific range arises organically e.g. for convolution we've landed around 2-4  
... different APIs have different ULP tolerance, although they're likely using similar values

<rachel> is precision testing necessary for all applications?

**Chai:** strategically, the best approach is to start with low tolerance (e.g. 1 ULP), and bump it based on real-world experience

**Rachel:** [from IRC] is precision testing necessary for all applications?

**Chai:** yes and no

... you can't test every single model

... testing the kernel, the implementation of the operators

... with an extensive enough set of kernel testing, the model itself should end up OK

... there are rare cases where the kernel tests are passing, but a given model on a given hardware will give slightly different results

... but the risks of that are lower if the kernels are well tested

**Ningxin:** regarding the ideal baseline, for some operators like convolution, there can be different algorithms

... what algorithm do you use for the ideal baseline?

... Applying this to WebNN may be more challenging since there is no reference implementation to use as an ideal baseline

**chai:** for DirectML, we implement the reference implementation using the conceptual algorithm in a CPU with double precision

... this is not what you would get from a real world implementation, but we use that as a reference

... For WebNN, we may end up needing a set of reference implementations to serve as a point of comparison

... there is no shortcut around that

... having some open source code available somewhere would be good

... but no matter what, you have to establish the ideal goal post

## Web Platform Tests

**FengDai:** I work on testing for WebNN API and have a few slides on status for WPT tests

*Slideset: fengdaislides*

*[slide 3]*

**FengDai:** 353 tests available for idlharess

... we've ported 800 test cases built for the WebNN polyfill to the WPT harness

... this includes 740 operator tests (340 from ONNX, 400 from Android NNAPI)

[WebNN WPT tests \(preview in staging\)](#)

**FengDai:** for 60 models tests use baseline calculated from native frameworks

... the tests are available as preview on my github repo

*[slide 4]*

**Anssi:** thanks for the great work - the pull request is under review, correct?

... any blocker?

**FengDai:** there are different accuracy settings, data types across tests

... this matches the challenges Chai mentioned

**Anssi:** the good next step might to join one of the WG meeting to discuss this in more details

**Chai:** thanks Bruce for the work! WPT right now relies on fuzzy comparison

... this means we'll need to change WPT to incorporate ULP comparison  
... hopefully that shouldn't be too much code change

**FengDai:** thanks, indeed

## 2

# Ethical issues in using Machine Learning on the Web

## [Ethical Web Machine Learning Editors draft](#)

**Anssi:** this is a document that I put in place a few weeks ago  
... the WG per its charter is committed to document ethical issues in using ML on the Web as a WG Note  
... this is a first stab  
... big disclaimer: I'M NOT AN EXPERT IN ETHICS

## [Ethical Web Machine Learning](#)

**Anssi:** we're looking for people with expertise to help  
... this hasn't been reviewed by the group yet  
... [reviews the content of the document]  
... ML is a powerful technology, enables new compelling UX that were thought as magic and are now becoming commonplace  
... these technologies are reshaping the world  
... the algorithms that underlie ML are largely invisible to users, opaque and sometimes wrong  
... they cannot be introspected but sometimes are assumed to be always trustworthy  
... this is why it is important to consider ethical issues in the design phase of the technology  
... it's important that we understand the limitations of the technology  
... the document then reviews different branches of ethics: information ethics, computer ethics, machine ethics  
... there is related work in W3C  
... e.g. the horizontal review work on privacy, accessibility  
... and the TAG work on ethical web principles

## [Privacy-by-design web standards](#)

## [Accessibility techniques to support social inclusion](#)

## [W3C TAG Ethical Web Principles](#)

**Anssi:** the document is focusing on ethical issues at the intersection of Web & ML  
... there are positive aspects to client-side ML: increased privacy, and reduced risk of single-point-of-failure and distributed control  
... it allows to bring progressive enhancement in this space  
... Browsers may also help increasing transparency, pushing for greater explainability  
... in the spirit of "view source"  
... I've looked at different literature studies in this space

**Rachel:** I'm interested in this and suggesting including a research into thinking of corporations

- ... many companies have efforts for responsible AI, so engaging with them is interesting
- ... focusing on human perspective of this may be a good focus
- ... can work with W3C Chapter to bring interested folks from that group into this discussion

.....  
*Minutes manually created (not a transcript), formatted by [scribe.perl](#) version slide-shower-184 (Tue Nov 30 23:12:07 2021 UTC).*

## Diagnostics

Succeeded: s/Fang/Feng

Succeeded: s/fferent/fference/

Succeeded: s|chaislides|https://lists.w3.org/Archives/Public/www-archive/2021Oct/att-0017/  
Conformance\_Testing\_of\_Machine\_Learning\_API.pdf

Succeeded: s/powerful document/powerful technology

Maybe present: Anssi, Chai, FengDai, Ningxin, Rachel, RafaelCintron