

Weak scalars proposal

NEP 50

What is the problem?

- NumPy has “value-based” promotion:

```
np.array([1], dtype=np.float32) + 4.5 -> float32  
np.array([1], dtype=np.float32) + 4e200 -> float64  
np.array(1., dtype=np.float32) + 4.5 -> float64
```

- This depends on it being “scalar” (zero dimensional):
 - All scalars (even 0-D arrays) often act as if they have no type attached!

```
np.array(1., dtype=np.float32) + 4.5 -> float64
```

- Even more confusing for integers!

Why is it like this?

```
np.array([1], dtype=np.float32) + 4.5 -> float32
```

- This is arguably convenient when working with specific dtypes!

```
np.array([1], dtype=np.float32) + np.float32(4.5) -> float32 🙄
```

Why is it like this?

```
np.array([1], dtype=np.float32) + 4.5 -> float32
```

- Convenient when working with specific dtypes (float32, int32)!

```
np.array([1], dtype=np.float32) + np.float32(4.5) -> float32 😞
```

- Also: We have a mess around 0-D arrays and scalars (but it is tedious to distinguish!)

Numeric literals should be special! But what else and to what degree?

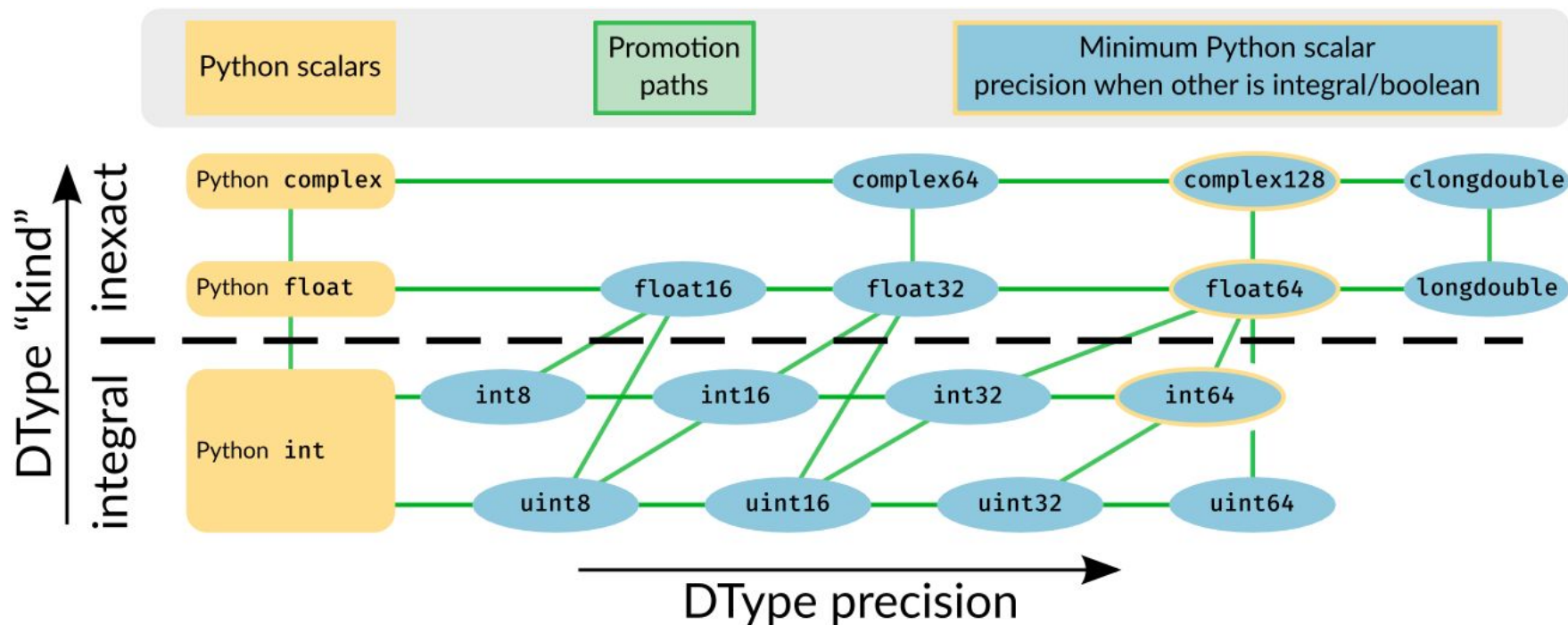
Current NEP 50 Proposal – Weak Python scalars

Expression	Old result	New result
<code>uint8(1) + 2</code>	<code>int64(3)</code>	<code>uint8(3)</code>
<code>array([1], uint8) + int64(1)</code> or <code>array([1], uint8) + array(1, int64)</code>	<code>array([2], uint8)</code>	<code>array([2], int64)</code>
<code>array([1.], float32) + float64(1.)</code> or <code>array([1.], float32) + array(1., float64)</code>	<code>array([2.], float32)</code>	<code>array([2.], float64)</code>
<code>array([1], uint8) + 1</code>	<code>array([2], uint8)</code>	<i>unchanged</i>
<code>array([1], uint8) + 200</code>	<code>array([201], np.uint8)</code>	<i>unchanged</i>
<code>array([100], uint8) + 200</code>	<code>array([44], uint8)</code>	<i>unchanged</i>
<code>array([1], uint8) + 300</code>	<code>array([301], uint16)</code>	<i>Exception</i>

Current NEP 50 Proposal – Weak Python scalars

Expression	Old result	New result
<code>uint8(1) + 300</code>	<code>int64(301)</code>	<i>Exception</i>
<code>uint8(100) + 200</code>	<code>int64(301)</code>	<code>uint8(44)</code> <i>and</i> <code>RuntimeWarning</code>
<code>float32(1) + 3e100</code>	<code>float64(3e100)</code>	<code>float32(Inf)</code> <i>and</i> <code>RuntimeWarning</code>
<code>array([0.1], float32) == 0.1</code>	<code>array([False])</code>	<i>unchanged</i>
<code>array([0.1], float32) == float64(0.1)</code>	<code>array([True])</code>	<code>array([False])</code>
<code>array([1.], float32) + 3</code>	<code>array([4.], float32)</code>	<i>unchanged</i>
<code>array([1.], float32) + int64(3)</code>	<code>array([4.], float32)</code>	<code>array([4.], float64)</code>

Current NEP 50 Proposal – Weak Python scalars



- This is not simple, please do have a look at the NEP:
<https://numpy.org/neps/nep-0050-scalar-promotion.html>
- There is a table highlighting some changes!

Most of this is implemented and usable

- I have done most of the impossible things!

```
export NPY_PROMOTION_STATE=weak  
np._set_promotion_state("weak")
```

- No, not thread safe (and I have no intention)
- Yes, there are still some bugs (but most likely you won't notice)

Design space and open questions 1

```
(float32(3) + 4.0).dtype == float32
```



```
np.add(float32(3), 4.0).dtype == ?
```

```
py_function(float32(3), 4.0).dtype == ?
```

```
(float32(3) + np.asarray(4.0)).dtype == float64
```

- JAX actually uses the weak logic for the last one too!
- There will *always* be inconsistencies
- Do we need ``asarray_or_literal()``?!
 - Maybe ``result_type`` is enough (other alternative?)

Design space and open questions 2

1. Scalars *could* behave different from arrays
 - (generally, I suspect this would be too confusing)
2. “Cast safety” is a hard and unsolved concept!
 - `np.add(uint8(3), 3, casting="equiv")` ?
 - `np.add(uint8(3), 300, casting="unsafe")` ?
3. Working with large Python integer 2^{1000} will be hard;
 - `np.int64(3) + 10**300` # Error!

Things to figure out! (hopefully not more)

- Cast safety for scalars!
 - There is probably no fully consistent solution.
- Test failures in NumPy:
 - Have been chipping away at it.
 - `np.arange(uint8(100))` of all is tricky (hopefully the solution is not)
- If and how to deal with Python level pattern (also in downstream):
 - `def function(a, b): a, b = np.asarray(a), np.asarray(b)`
- If we need to do things (and if what) to make transition easier.

User Impact and Alternatives

Changes affect mainly **end-users** and **not** libraries! Mostly, I expect changes to not matter, but they will break scripts in hard to track down ways!

- Affects *many* users but also many will not be affected:
 - Array math effectively “weak” scalars!
 - Array math results will be more exact precision usually
 - Floating point comparisons may change results!
 - Code using default DTypes (integer/floats) is not be affected.
- Scalar math is likely the main problem:
 - *Most* paths will at least give a warning (float math) or error (integer math)
 - ```
arr = np.arange(100, dtype=np.uint8) # storage array with low precision
value = arr[10]
use "value" without considering where it came from
value * 100 # Overflow warning (luckily)
```
- Large integer math will become harder.

# Alternatives

- JAX style `np.asarray(3.0)` is still “weak”
  - I doubt this is feasible but...
- Strong scalars:
  - Python float is float64, Python int is “default integer”.
  - Only 100% consistent solution, but gives up on all the nice things
- Make scalars special (but how?)
- Give up :)